ABSTRACT

Title of Dissertation:	PARTICIPATION IN CLIMATE CHANGE ADAPTATION: THE ROLE OF SOCIAL NETWORKS IN SUPPORTING LEARNING AND COLLECTIVE ACTION
	Jose Daniel Teodoro Morales, Doctor of Philosophy, 2020
Dissertation Directed by:	Professor Christina Prell, Department of Geographical Sciences
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Climate change is a complex problem affecting the world in different ways and posing challenges at varying governance levels. It is widely acknowledged that broad stakeholder participation is needed to adapt to increasing climate impacts. However, interactions between stakeholders are complex and not enough is known about the social processes that support stakeholder participation or how to measure its effectiveness. The main goal of this dissertation is to increase the understanding of stakeholder participation in addressing climate change problems. Using the State of

Maryland (USA) as a case study, I (1) evaluate the magnitude of climate change impacts and map the stakeholder landscape in this region, and (2) I focus on a local participatory process in the eastern shore of the Chesapeake Bay, the Deal Island Peninsula Partnership (DIPP), to study how stakeholder networks facilitate learning and collective action. I found the Chesapeake Bay is experiencing severe impacts from sea-level rise, scientists and state government produce more data and indicators at larger scales, while fewer data are produced at the local level where is needed. Increasingly, participatory approaches are being employed to bridge the knowledge gap between experts, scientists, and local stakeholders. Moreover, I found that DIPP stakeholder views are predicted by their social networks of mutual understanding, respect, and influence. Finally, by modeling the co-evolution of mutual understanding ties, co-attendance, and climate change perceptions, I found that stakeholder participation enables stronger and denser social networks of mutual understanding, yet these ties do not facilitate changes in perceptions. These results suggest that fostering mutual understanding among a diverse group of stakeholders may be more relevant for collective action than changing their perceptions. This dissertation provides empirical evidence that stakeholder participation is important in climate adaptation policies and contributes to the development of measures for stakeholder participation effectiveness.

PARTICIPATION IN CLIMATE CHANGE ADAPTATION: THE ROLE OF SOCIAL NETWORKS IN SUPPORTING LEARNING AND COLLECTIVE ACTION

By

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Dissertation submitted to the faculty of the graduate school of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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DEDICATION

To my parents:

Ana Leticia Teodoro & Jose Francisco Teodoro

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

ACRONYM	DEFINITION
BMPS	Best Management Practices
CCA	Climate Change Adaptation
DIP	Deal Island Peninsula
DIPP	Deal Island Peninsula Project
EM	Environmental Management
ESLC	Eastern Shore Land Conservancy
FEMA	Federal Emergency Management Administration
GHG	Greenhouse Gas
GOF	Goodness of Fit
ICRA	Integrative Coastal Resiliency Assessment
IAN	Integration and Applied Network
MCCC	Maryland Commission on Climate Change
MD	Maryland (state)
MDSG	Maryland Sea Grant
NGO	Non-Governmental Organization
SAOM	Stochastic Actor-Oriented Model
SLR	Sea-Level Rise
SNA	Social Network Analysis
SWAT	Soil Water Assessment Tool
WIP	Watershed Implementation Plan

LIST OF PUBLICATIONS

The work carried out for this dissertation research has resulted in a number of conference presentations and peer-reviewed publications, ordered by the chapter in which they are presented in this thesis.

Chapter 2

The contents of chapter 2 are published in Climate:

Teodoro, J. D., & Nairn, B. (2020). Understanding the Knowledge and Data Landscape of Climate Change Impacts and Adaptation in the Chesapeake Bay Region: A Systematic Review. Climate, 8 (4), 58. DOI: https://doi.org/10.3390/cli8040058

Chapter 3

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Chapter 4

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1. INTRODUCTION

Anthropogenic climate change is a threat to human livelihoods and the sustainability of civilization into the future (Hayhoe et al., 2018). Climate-related risks to human and natural systems have already been observed, and changes in the ocean and land ecosystems and the services they provide are projected to increase due to global warming (Hoegh-Guldberg et al., 2018). Addressing this level of threat requires flexible, adaptive strategies based on a holistic understanding of climate change, its drivers and impacts, and the governance structures at varying scales (Pasquier et al., 2020; Teodoro and Nairn, 2020). Stakeholder participation is increasingly seen as a key method in developing a holistic understanding of complex environmental problems (Baird et al., 2016; Calliari et al., 2019; Pasquier et al., 2020; van Aalst et al., 2008). In this dissertation, I focus on the Chesapeake Bay, Maryland, to investigate the physical risks posed by climate-driven hazards to coastal communities and study how stakeholders develop social networks to facilitate learning and collective action.

1.1 MOTIVATION

1.1.1 GLOBAL CHANGE AND COASTAL REGIONS

There is a broad consensus that global climate is warming due to anthropogenic greenhouse gas emissions (Hoegh-Guldberg et al., 2018). However, climate changes affect different regions of the planet in different ways, which makes national and sub-national governments responsible for designing adaptation and mitigation actions to address the relevant concerns of their societies and geographies (Dannevig et al., 2012; Epanchin-Niell et al., 2017). One type of geography that is experiencing, and will continue to experience, climate impacts are coastal regions, which are susceptible to the effects of sea-level rise (Boesch et al., 2018). Coastal areas the geographic focus of this dissertation, mainly because of their significance to society in general. Across the world, 2.4 billion people (about 40% of the world's population) lived in coastal or near water urban areas as of 2017 (United Nations, 2017). Marine resources are mayor economic hotspots, accounting for $100 billion per year and about 260 million jobs to the global economy (United Nations, 2017). Moreover, sea-level rise (SLR) is a constant threat to coastal communities and exacerbates the impacts of hurricanes and tropical storms, causing major damage due to flooding (Bhattachan et al., 2018; Boateng, 2012; Boesch et al., 2018; Brooks et al., 2006; Sweet et al., 2014). The economic impact of SLR will dramatically increase by 2100, considering the IPCC climate scenarios, and is expected to account for 4% of the global gross domestic product if no adaptation strategies are implemented (Schinko et al., 2020). In these respects, coastal regions are among the most vulnerable geographies to climate impacts.

1.1.2 POLICY AND MANAGEMENT

There is a broad understanding between government, academia, and civil society organizations that responding to climate problems will require collaboration among invested stakeholders. The development of climate adaptation policies aimed at increasing resilience to climate change must be based on a mix of scientific and local knowledge to harness the full potential societies (Berkes, 2017). The goal of policy-making in the face of increasing rates of climate change is to reduce the risk to human lives and natural ecosystems by increasing adaptive capacity to existing and projected impacts (Cutter et al., 2013).

1.2 BACKGROUND

1.2.1 STAKEHOLDER PARTICIPATION

In this dissertation, I focus on the role of stakeholder participation in coastal climate change adaptation. *Stakeholder participation* is defined as the deliberative process in which a diverse set of relevant actors engage in an iterative, ongoing set of discussions and/or activities to develop a deeper understanding of an environmental management issue and potentially, arrive at a more suitable governance solution (Anggraeni et al., 2019; Reed, 2008). Stakeholder participation is an emerging field, which has mainly focused on the collaboration of actors involved in the management of a *common pool resource* (Agrawal, 2002; Ostrom, 1990; Ostrom et al., 1994). Climate change can be considered a common pool resource requiring of a collective management scheme to responsibly administer its impacts and potential benefits. Naturally, the climate adaptation community has drawn from the natural resource management literature in search of management science in response to climate change. There is a wealth of literature on stakeholder participation, from stakeholder analysis (Hauck et al., 2016; Prell et al., 2009; Zedan and Miller, 2017), environmental and social outcomes of participation (Armitage et al., 2011; de Vente et al., 2016; Lauer et al., 2017; Shackleton et al., 2019), different types of participation (Meadow et al., 2015), to the evaluation of participatory process performances (Cvitanovic et al., 2019; O'Connor et al., 2019; Trimble and Berkes, 2013). One clear thing is that this field is being driven by the need to generate effective and efficient climate adaptation management.

1.2.2 SOCIAL NETWORK ANALYSIS

One fundamental aspect of stakeholder participation is the inclusion of a diversity of actors (Reed, 2008). These may include local residents and representatives from governments, academia, private enterprises, and civil society organizations. The premise of stakeholder participation is to facilitate the interaction and bonding of stakeholders in order to develop a greater understanding of the impacts of climate change by the sharing of knowledge from each stakeholder. Environmental management studies indicate that engaging stakeholders in participatory processes provide unique opportunities for stakeholders to interact face-to-face and share their views (Daniels and Walker, 2001; Lumosi et al., 2019; Paolisso et al., 2019). Such interactions form channels through which information can flow (Ernoul and Wardell-Johnson, 2013), and mutual understanding to occur (Rist et al., 2006). In addition, these interactions can lead to the formation of collaboration ties (Anggraeni et al., 2019; Baird et al., 2018; Bodin and Crona, 2009; Kochskämper et al., 2016; Masuda, 2007), and ties based on trust and/or respect (Cundill and Rodela, 2012; García-Nieto et al., 2019). These social processes can be studied through the use of social network analysis (SNA).

In this dissertation, I look at stakeholder participation through a network perspective. By studying the network structure and the role networks play on stakeholder learning, I hope to advance the knowledge of stakeholder participation and support climate change adaptation efforts.

1.2.3 SOCIAL LEARNING

Specifically looking at the association between stakeholder networks and social learning—the change in understanding by individuals as a result of stakeholder participation—addresses questions about the effectiveness of networks in supporting learning processes. Moreover, identifying the effect of different types of networks (e.g., communication, mutual understanding, mutual respect, mutual influence) on learning can provide valuable insights into the social mechanisms that take place during the participatory process and inform future research and practices. As such, this dissertation seeks to contribute to the literature on social learning, specifically within the stakeholder participation and climate change adaptation spaces, where learning is part of a broadly untested theory. The existing literature suggests that ongoing participation among stakeholders leads to network formation, which in turn facilitates social learning and collective action (Kochskämper et al., 2016; Schwilch et al., 2012; Trimble and Berkes, 2013). For the most part, there is minimal empirical evidence of these processes taking place, and none to my knowledge that accounts for the social networks in learning. Nonetheless, social learning is arguably one of the most important aspects and outcomes of stakeholder participation, premised in the transfer of knowledge among stakeholders that must lead to cognitive learning. Moreover, the relation between social learning and collective action—defined as the coordination of efforts among stakeholders to achieve a common goal when the self-interest of each stakeholder would be inadequate to achieve the desired outcome

(Tompkins and Adger, 2004)—is not fully understood; another aspect that I address in this dissertation.

1.3 RESEARCH OBJECTIVES

The overall goal of my research is to explore how stakeholders in climate change adaptation develop social networks among them and how these social relations support learning and collective outcomes. Three research objectives will help reach this goal: (1) conduct a systematic literature review of climate change impacts in the Chesapeake Bay to understand the knowledge and institutional landscape, (2) evaluate the social networks of stakeholder engaged in a participatory process in a coastal region in the Chesapeake Bay, and (3) identify the social processes that drive network-formation and perception-formation behavior among stakeholders in a coastal community in Maryland.

1.4 DISSERTATION OUTLINE

This dissertation is organized as follows: Following this introduction, Chapter 2 first shows a large dataset of different scientific, non-academic, and policy publications I reviewed. It discusses the characteristics of the climate change literature in Maryland and the emerging themes in the literature regarding existing and needed climate adaptation data and indicators.

Chapter 3 first describes the literature on stakeholder participation in natural resource management and climate change adaptation, focusing on the overlaps of social network analysis and participation. Then, I introduce an evaluation framework using social network analysis to predict perceptions of climate change in participatory settings. Lastly, I apply the evaluative framework on the case of the Deal Island Peninsula, a region in the eastern shore of the Chesapeake Bay. Statistical models were used to conclude that social relations among stakeholders that are based on mutual understanding, respect, and influence have a positive and significant relationship with stakeholder perceptions of climate change.

Chapter 4 first evaluates the theory and literature on the social processes that guide stakeholder network and perception behavior in participatory settings. I present four literature-based hypotheses and use a stochastic actor-oriented modeling (SAOM) framework to test them on the Deal Island Peninsula dataset. Finally, I present the results of these hypotheses and summarize the contribution of the case study to the larger literature and theory of stakeholder participation.

Finally, Chapter 5 synthesizes the outcomes of the three studies and discusses the similarities, differences, and limitations of the modeling techniques used in Chapters 3 and 4. Also, I provide details on how the findings of this study may affect the future of stakeholder participation in climate change adaptation.

2. UNDERSTANDING THE KNOWLEDGE AND DATA LANDSCAPE OF CLIMATE CHANGE IMPACTS AND ADAPTATION IN THE CHESAPEAKE BAY REGION: A SYSTEMATIC REVIEW

ABSTRACT

Climate change is increasingly threatening coastal communities around the world. This article reviews the literature on climate change impacts and adaptation in the Chesapeake Bay region (USA). We reviewed both climate impacts and adaptation literature (n=283) published in the period 2007 – 2018 to answer the questions: (i) how are indicators of climate impacts measured and reported by different types of authors (e.g., scientists, government, and NGOs), document types (e.g., academic articles or reports), and geographic focus (e.g., State, region, county, or municipal level)? (ii) what are the current approaches for measuring the most pressing climate impacts in the Chesapeake Bay? We found that scientists produce the most amount of data but are increasingly shifting towards engaging with practitioners through reports and online resources. Most indicators focus on the Chesapeake Bay scale, but data is most needed at the local level where adaptive policies are implemented. Our analysis shows emerging approaches to monitoring climate hazards and areas where synergies between types of authors are likely to increase resilience in the 21st century. This

review expands the understanding of the information network in the Chesapeake Bay and explores the institutional landscape of stakeholders involved in the production and consumption of environmental and social change data. The analysis and insights of this review may be extended to similar regions around the planet experiencing or projecting similar climate hazards to the Chesapeake Bay.

2.1 INTRODUCTION

Anthropogenic climate change is a threat to the livelihood of humans and the sustainability of our civilization into the future (Hayhoe et al., 2018). Climate-related risks to human and natural systems have already been observed, and changes in the ocean and land ecosystems and the services they provide have already changed due to global warming (Hoegh-Guldberg et al., 2018). Climate changes affect different regions of the planet in different ways, which demand national and sub-national governments to design adaptation and mitigation actions to address the relevant concerns of their society and geography (Dannevig et al., 2012; Epanchin-Niell et al., 2017). In the United States, climate change is predicted to have cascading effects in the social, economic, and ecological systems, and it is estimated that climate-related impacts on the U.S. economy may results in a 10% shrinkage by the year 2100 (Martinich et al., 2018). Even within the United States, climate change will have varying impacts; for example, coastal areas are particularly susceptible to the effects of sea-level rise (SLR) and arid areas of the southwest prone to drought and wildfires (Hayhoe et al., 2018). Developing adaptation policies and strategies based on scientific and local knowledge mixed with the use of modern technologies have the potential to reduce the risk of climate change to human lives and natural ecosystems and strengthen our economic and social systems in anticipation to projected impacts (Cutter et al., 2013). However, the processes that enable successful adaptation to climate change, those that support democratic stakeholder participation and consensus-building, are yet to take hold of mainstream local environmental politics.

Adapting to the climate's imminent threats is still an ongoing challenge and largely a geographic-specific issue. The multi-scale governance—the dynamic vertical structure of communication and power that may scale from a municipal boundary to the government of a state or nation—of a place that is vulnerable to climate impacts must transform itself into an efficient system. Scientific literature suggests that the adaptive capacity of vulnerable populations, cities, and counties largely depends on governance structure (Mandryk et al., 2015; Morrison et al., 2017), local and scientific knowledge integration (Glaas et al., 2010; Vogt et al., 2016), and establishing strong social networks (Crona and Bodin, 2010). Indeed, there has been an increase in the scientific and management information on climate change in the last decade but progress in the adaptation space remains a challenge for many communities and local governments (Chesapeake Bay Program, 2015). The vastness of information often leaves stakeholders overwhelmed and unsure how to understand their community's resilience. Thus, this report reviews the literature on climate adaptation indicators from 2007 – 2018 with a geographic focus of the Chesapeake Bay (Maryland) in the United States.

This article focuses on the Chesapeake Bay because it is a region already experiencing major climate-related impacts of sea-level rise, more hurricanes and tropical storms, and is projected to get worse throughout the 21st century. Adequately responding to climate hazards and increasing local resilience requires the active participation of stakeholders across multiple levels of the state of Maryland's government (Hileman and Lubell, 2018) and engagement of the local, scientific, and non-profit communities. Adaptation is more challenging when the institutional landscape of actors is made up of many universities, research institutes, civil organizations, government agencies, and community organizations. Thus, an important challenge in adaptation science is the compilation and synthesis of all available information, distinguishing the nuanced differences between author types, document types, and geographic scale.

Following the conclusions by the Maryland Commission on Climate Change (MCCC), we agree there is a need for a cohesive research agenda for the state of Maryland and the Chesapeake Bay that communicates the science needed to support state and local decision-making (MCCC Maryland Commission on Climate Change, 2016). We reviewed the available literature by multiple author types (local, county, state government, non-governmental research and outreach organizations, as well as scientific journal publications) in order to contribute to the understanding of climate adaptation science and practice to this date. We do so by asking the following questions: *(i) how are indicators of climate impacts measured and reported by different types of authors, document types, and geographic focus? (ii) what are the* *current approaches for measuring the most pressing climate impacts in Maryland and the Chesapeake Bay?* We close with research and practitioner-focus recommendations on emerging indicators of climate adaptation and outlook. The findings and conclusions of this review article are meant to advance the understanding of climate adaptation and resilience in the State of Maryland and add to the development of a holistic framework for climate resilience measurement across multiple regions.

2.2 MATERIALS AND METHODS

A qualitative review analysis was employed on scientific and non-academic literature to evaluate existing data on the use of indicators and metrics to track the trends of climate change impacts within the state of Maryland. This section describes the study area, the methodology used to make the final determination of the article sample, data collection, and the qualitative approach used to analyze and synthesize the data.

2.2.1 CLIMATE CHANGE IN MARYLAND, USA

Coastal areas in the United States are at risk of drought and flooding, shoreline erosion, salt-water intrusion, and other climate-related hazards (Burkett and Davidson, 2012). The Chesapeake Bay is the largest estuary in the United States and one of the most diverse. Maryland's over 4,000-miles of shoreline, and its network of tidal rivers and the Atlantic coast, makes the state particularly susceptible to flooding and erosion brought on by tides, storms, and increasingly SLR (Pyke et al., 2008). These climate hazards are already impacting coastal communities in Maryland and are expected to worsen (Ambrette, 2017; Epanchin-Niell et al., 2017; Najjar et al., 2009; Schulte et al., 2015). Nuisance flooding (also referred to as sunny-day flooding or high tide flooding) is projected to increase in frequency due to global SLR, and by 2100 high tide flooding will occur ‘every other day’ or more often (Sweet et al., 2018). Scenarios for CO_2 emissions suggest the region is likely to experience significant changes in climatic conditions in the 21st century, including increasing CO2 concentrations by 50 to 160 percent, increasing water temperature by 2° to 6°, and fluctuating precipitation patterns (Pyke et al., 2008).

Maryland has historically been at the forefront of states acting to address drivers and consequences of climate change. The policy record of Maryland shows that the state has directed agencies at all levels of government, academic, and private institutions to understand and respond to environmental conditions like sea-level rise, clean air, and land conservation (MCCC Maryland Commission on Climate Change, 2016). In 2013, Maryland passed into state law the Maryland Commission on Climate Change (MCCC), initially formed in 2007 by Executive Decree (01.01.2007.07) to provide objective legislative advice and research support. The creation of the MCCC signaled the level of concern and urgency felt by Marylanders, many who have inhabited the Chesapeake Bay for many generations and who increasingly consider climate change among the major threats to the state (Akerlof et al., 2015). But the growing dangers of anthropogenic climate change to the state has fueled a surge of efforts to combat climate hazards with robust science and policies that incorporate the participation of multiple stakeholders (Ambrette, 2017).

We chose to focus on the state of Maryland because of its historical track record of adopting policy and promoting collaborations to combat climate change, its wealth of information on climate-related hazards, and because it exemplifies specific challenges faced by large coastal regions impacted by coastal-specific climate hazards (e.g., SLR, coastal ecosystem changes, and stormwater management in a mostly agricultural watershed).

2.2.2 DOCUMENT SELECTION

We collected reports and articles from scientific and non-academic literature. Scientific articles published in peer-reviewed journals were collected from the Web of Science using the following code: “TS = (("Maryland" OR "Chesapeake Bay") AND (Climat* OR Indicator*) AND (Resilience OR Hazard OR Exposure OR Impact OR Susceptibility OR Adaptation OR Coping OR Capacity OR Mitigation)),” and the search was restricted to include only articles published between 2007 – 2018; the period since the creation of the MCCC. Non-academic literature was searched using the same keywords in the Google search engine, following the approach by Godin et al. (Godin et al., 2015). The title, abstract, and keywords for each search result—scientific and non-academic literature—were scanned for geographic and topic relevance following the procedure described in *I.1 Inclusion Criteria*. From the initial sample, excluding duplicates, 717 documents were screened full-text to determine if they contained data and indicators. A final sample of 283 articles was reviewed and included for qualitative coding (Figure 1).

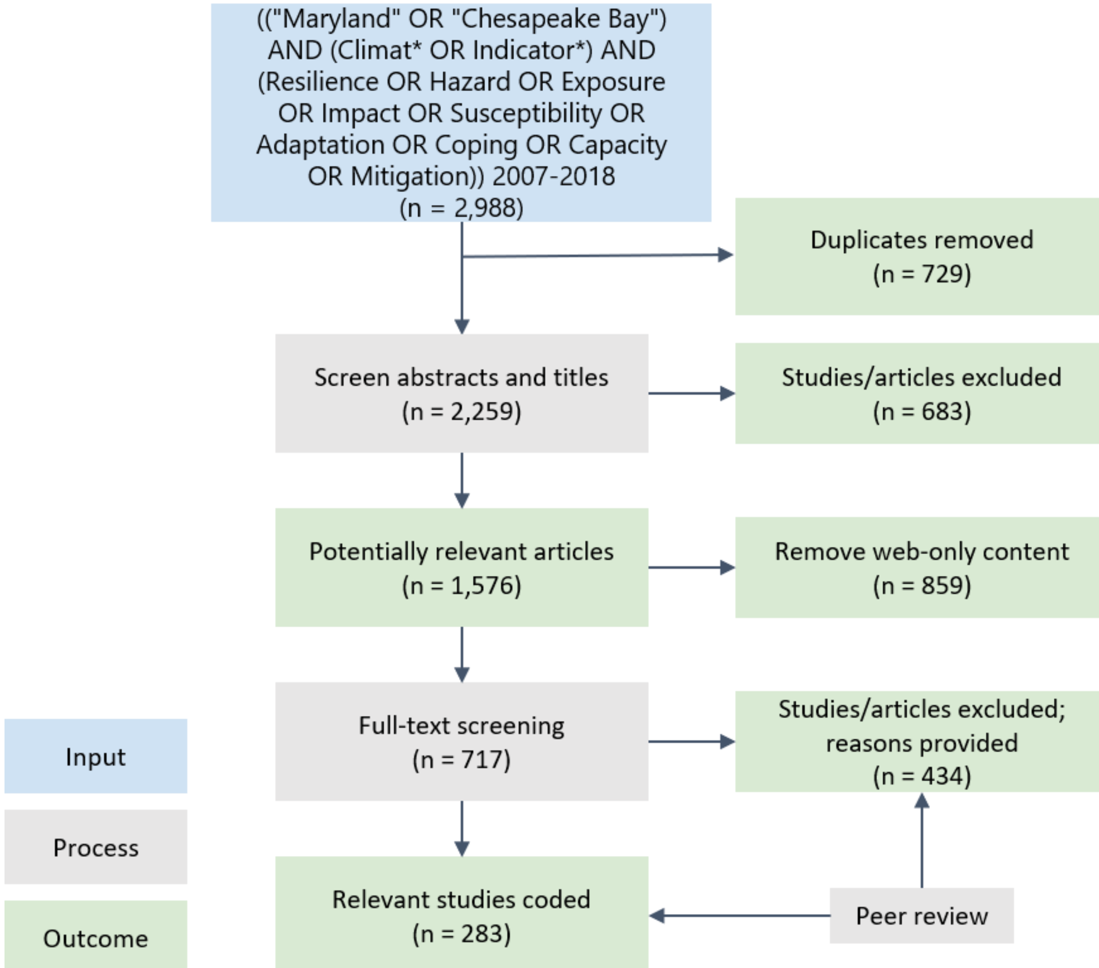

Figure 1: Document selection process for systematic review

2.2.3 QUALITATIVE CODING AND ANALYSIS

Drawing from the methodology of Saldaña (Saldaña, 2015), we identified the broader trends and themes in the literature concerning the aspects of climate hazards and adaptation efforts in Maryland. Using the qualitative coding software NVivo 12.3 (Richards, 2005), each document was first coded for its source information (the type of author, type of document, and geographic focus). Then every instance in a document where an indicator or dataset was identified would be coded based on six aspects: (1) what aspect of climate change is being measured, (2) the geographic scale of that indicator, (3) type of information included, (4) type of indicator (i.e., lagging, coincident, or leading), (5) which aspect of the resilience framework it addresses, and (6) if it pertained to social characteristics or demographics. Also, optional codes were used to capture the instances where a clear methodology for an indicator was provided. In sum, a total of 139 unique thematic codes made the coding schema applied in this review (*I.2 Coding Schema*).

After all included documents were coded, we carried out a qualitative analysis following the methodology developed by Petticrew and Roberts (Petticrew and Roberts, 2008), which follows three steps: First, all documents were organized into cases based on the type of author, geographic focus, and whether the document was a scientific or non-academic publication. Second, we analyzed the information found within each case to help identify emerging themes within each case (e.g., the focus on climate adaptation by different types of authors). The third step involved analyzing the information across cases to understand the cross-cutting themes throughout the document database. The combined process provides a comprehensive qualitative analysis of the literature on climate change resilience and adaptation in Maryland.

2.3 RESULTS

2.3.1 DATASET OVERVIEW

The final sample of documents that met the inclusion criteria resulted in 283 files. Visualized using a Sankey diagram, it is clear that several large clusters are present (Figure 2). In terms of geographic focus, the Chesapeake Bay is the geographic focus of about one-third of the documents. Of these, almost all are written by academic scientists, with about one-third of the Chesapeake Bay documents being scientific articles and another third being reports. As a group, the output of academic scientists is overwhelmingly focused on the Chesapeake Bay.

Figure 2: Descriptive distribution of a type of author, b type of document (i.e., Science article, report, presentation, or online resource), and c geographic focus of the document.

About one-third of the documents focus on the state level. These are predominantly written in report form by state and national governments. The remaining third of documents are spread among the municipal, country, regional, national, and global levels, with the majority of documents addressing the municipal and county levels. These are almost all in report form and authored mostly by county and municipal governments and NGOs.

The distribution of author types within our sample and the means of communicating information to the wider public show the complex institutional landscape of climate adaptation in the Chesapeake Bay. The largest author type within our sample are scientists (42%), who author almost the same number of scientific articles and non-academic reports. When looking at document types, the most form of climate adaptation and resilience literature in Maryland are reports; covering 64% of the sample. It may be worth mentioning that almost all documents authored by County-level authors were in report form and the remaining sliver were presentations.

When exploring our sample based on the year of publication, the amount of documents show an upward trend with a larger number of documents being published in the latter part of the sampling period (Figure 3). Most of the increase after 2014 originates in academic articles about the Chesapeake Bay. An outlier in the trend is the year 2008, in which a large number of documents were published. Most of the reports were authored by the state government and scientists with a state-wide geographic focus. This increase may be explained by the creation of the Maryland Commission on Climate Change on 2007, which marked the beginning of scientific and political attention to climate change impacts in Maryland and the Chesapeake Bay.

2.3.2 FOCUS ON INDICATORS AND DATA

Within every document we found data, metrics, or indicators that captured quantitative information about climate change impacts and responses. There are well known reviews of the impacts affecting the Chesapeake Bay (Pyke et al., 2008) and the United States (Bierbaum et al., 2013). Therefore, we do not claim this section provides new information in general. However, the contribution of our review in this section should be considered with a lens of available quantitative measures/metrics. These data may be used to development better climate resilience and adaptation indicator systems. It is not always possible to collect data on climate hazards and impacts that are qualitatively well known to the local communities and resource managers in the Chesapeake Bay. An example of this is the finding that County-authored documents often described the vulnerability and risk of increasing river discharge flows, but it was the scientific-authored documents that provide quantitative data and analysis of those impacts. Therefore, in this section we elaborate on the information of climate change and impacts within our sample limited to those that met the substantive data/indicators criteria.

Communities around the Chesapeake Bay already experience tangible impacts to their infrastructure, social life, and economy due to climate hazards (Ambrette, 2017). The low-lying coastal geography of Maryland makes the region particularly vulnerable to mean sea-level rise (SLR) (Boesch et al., 2018, 2013; Sweet et al., 2018). Moreover, current and projected changes in precipitation patterns in Maryland and the Chesapeake Bay watershed are expected to add pressure to stormwater systems and increase agricultural runoff (Harris and McElfish, 2017; Hoss et al., 2016; Renkenberger et al., 2017). In turn, changes in the water quality and temperature in the bay pose considerable risks to the health of marine ecosystems, which are likely to have adverse economic and social impacts on coastal communities (Glandon et al., 2018; Glaspie et al., 2018, 2017; Glick et al., 2008b). The economic underline of many climate impact data is not surprising, given that the Chesapeake Bay has long been an economically productive source of income; fish, shellfish, and oysters provided the State of Maryland with a $63 million in 2013 (MCCC Maryland Commission on Climate Change, 2016). Another focus on climate impact data, albeit not very prominent within our sample, is the association between climate change (e.g., rising temperature and more frequent hurricanes/storms) and aspects of human health (e.g., hospitalization rates and incidence of water-borne diseases). Taken together, the concert of interconnected impacts in the Chesapeake Bay pose significant challenges to researchers and practitioners in developing adequate responses to climate change.

Sea-level Rise (Aquatic-type indicators)

Indicators focused on aquatic climate impacts are found in most documents (Figure 4). Aquatic indicators include coastal and river flooding, marine species health and abundance, SLR, stream flows, water quality among others. In the Chesapeake Bay, SLR and related impacts are the dominant theme in the Aquatic type datasets and indicators. SLR in the Chesapeake Bay is projected to reach between 2 – 6 ft. in this century, which is higher than the global mean SLR (Boesch et al., 2018; MCCC Maryland Commission on Climate Change, 2016; Sweet et al., 2018). According to the Maryland Commission on Climate Change (Boesch et al., 2013), even the most optimistic SLR scenarios are projected to have considerable impacts on the Bay communities. Indicators and data within the Aquatic theme, specifically SLR and coastal/river flooding indicators were dominant across all types of authors (i.e., government, NGO, and academic authors), and at all geographic levels (i.e., municipal, county, state). Most of these indicators were found in reports.

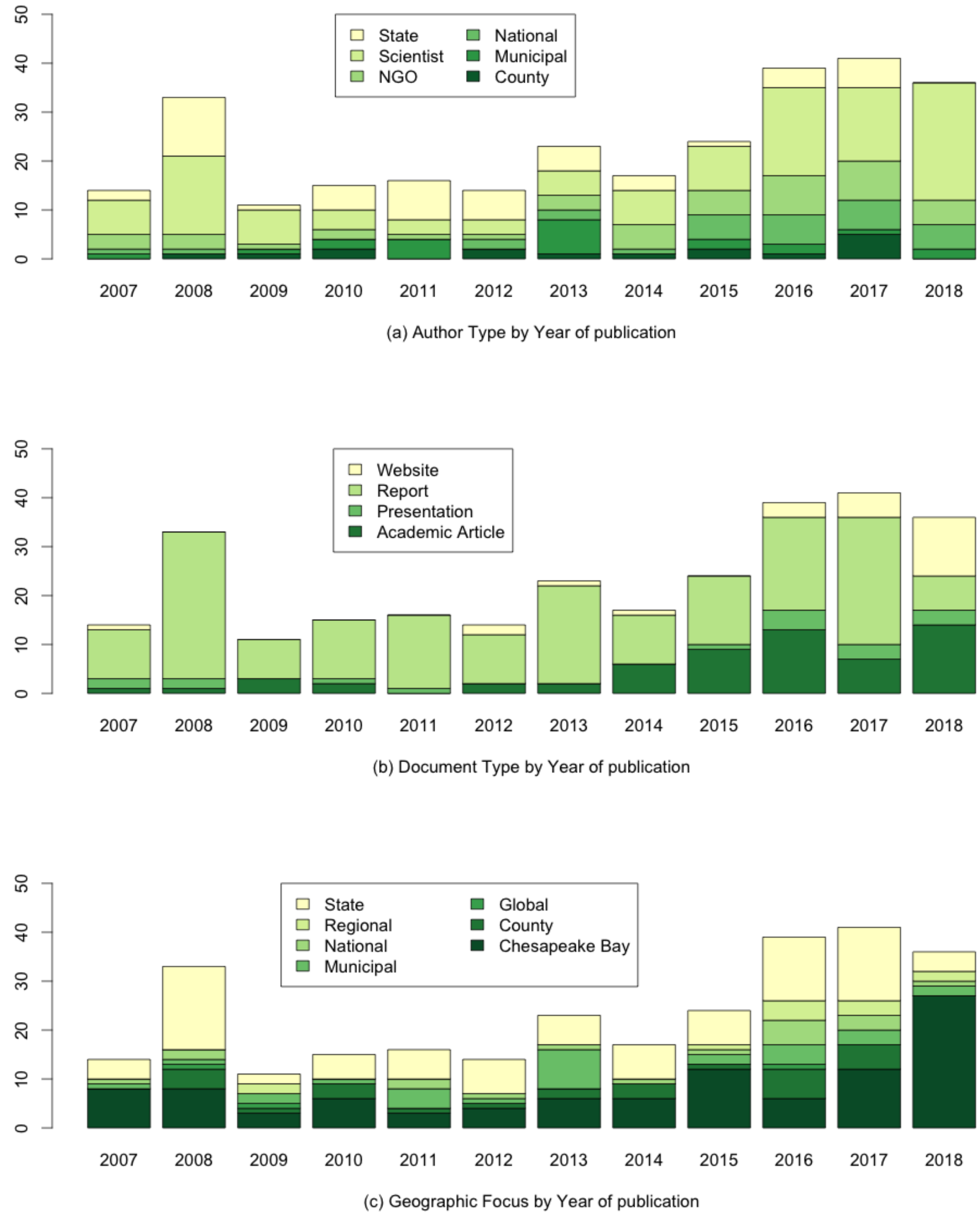

Figure 3: Year of publication of sampled documents by (a) type of author, (b) type of document, and (c) geographic focus of document.

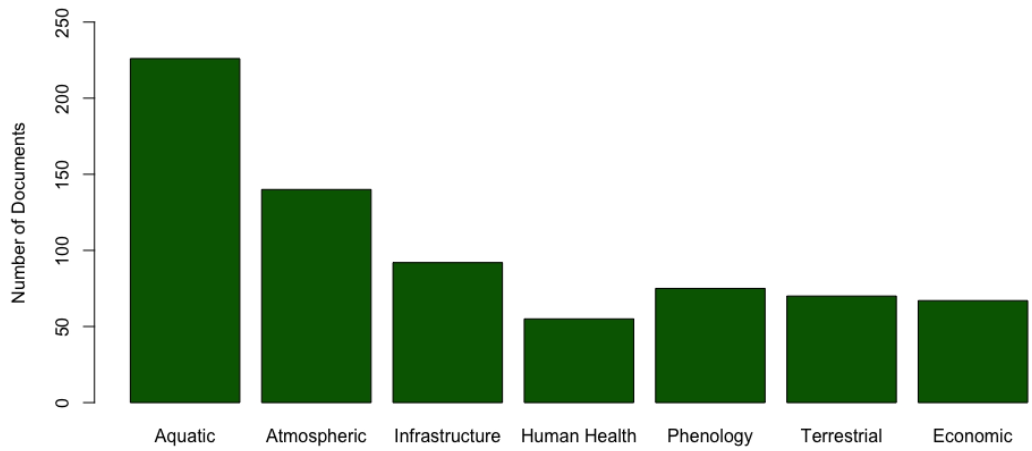

Figure 4: Number of documents that contained different climate change impact indicators.

When looking at the format of SLR data and indicators available, many documents focus on the economic effects SLR will have on the future based on different climate projections (Anne Arundel County, 2010; Calvert County, 2017; Somerset County, 2008; Talbot County, 2017). Flooding of coastal areas and floodplains, either by increased precipitation (Montgomery County, 2009; Renkenberger et al., 2016), chronic sea-level rise (Ambrette, 2017; Boesch et al., 2018, 2013), or storm surges (Kent County, 2014), will damage private and public infrastructure and cause large economic loss. The risk and impacts of SLR are commonly measured with detailed flood projection maps based on different climate scenarios, and a spatial assessment of the number of buildings and infrastructure that would be affected (Calvert County, 2017; Kent County, 2014; Talbot County, 2017). Methods employed to measure the projected spatial risk of SLR, include several of the Federal Emergency Management Administration (FEMA)'s flooding and hazard assessment tools like HAZUS-MH. These types of analyses are useful for identifying and prioritizing the most vulnerable areas to SLR and flooding from storms and hurricanes across multiple locations and estimating the cost of damage to infrastructure (Harris and Brownlee, 2016; Johnson, 2014; Spanger-Siegfried et al., 2017). As a result, increasing flood protection and adapting building codes in response to projected SLR-driven impacts in 2050 and 2100 are relevant considerations for some coastal counties in Maryland (ESLC Eastern Shore Land Conservancy, 2016; Somerset County, 2015; Talbot County, 2017; Worcester County, 2014). Improving the resolution of these map-based analyses will likely empower local-level resource managers and community members to take, and measure, adaptive actions.

The Chesapeake Bay is a large estuarine system with wetlands and marshlands. As such, several documents (Anderson and Barnett, 2017; Cross et al., 2016; Dunn and Stamey, 2010; Glick et al., 2008b, 2008a; Kane, 2013) provide in-depth analyses of the effects SLR is projected to have on coastal habitats, some of which are projected to lose between 58% to 69% of their habitat by 2100 (Glick et al., 2008b). Even though major changes in the composition of coastal ecosystems can be expected, the implications of those changes for humans or marine life are not fully understood (Maryland Sea Grant, 2015). Understanding the changes of coastal habitats in relation to how that affects humans can facilitate the development of adaptive strategies that enable the adaptive potential of those habitats (Maryland Sea Grant, 2015; World Bank, 2016).

Precipitation and Nutrient Loading in Watershed Hydrology

Predictions of precipitation changes in the Chesapeake Bay watershed in this century are less understood than temperature projections (Pyke et al., 2008). However, data found in the reviewed documents show an increase in precipitation compared to current conditions (Hawkins, 2015; Kang and Sridhar, 2018; Renkenberger et al., 2016). Renkenberger et al. (Renkenberger et al., 2016) estimate changes in precipitation to increase between 25% - 30% by the end of the century. Other sources show more conservative predictions: Hawkins (Hawkins, 2015) predicts a smaller increase of 5.2% to 15.2%, and Pyke et al. (Pyke et al., 2008) predicted 3% to 8%. In general, precipitation is likely to increase during winter (less as snow) and decrease during summer and fall (Hawkins, 2015; Wagena et al., 2018). In Maryland, and the Chesapeake Bay, increasing precipitation contributes to inland flooding (Kent County, 2014), higher non-point source sediment and nutrient pollution into the Chesapeake Bay watershed (Kang and Sridhar, 2018; Renkenberger et al., 2017, 2016), higher soil erosion (Segura et al., 2014), impacts on agricultural yields (Montgomery County, 2013; Williamson et al., 2008), increases pressure on rain and wastewater management systems (Harris and McElfish, 2017; Pyke et al., 2008), increases in the risk of dam failures (Prince George’s County, 2010), and contributes to growth of water-borne diseases (Soneja et al., 2016a; Williamson et al., 2008). Moreover, the seasonal variability of projected precipitation may increase droughts in the summer months (Montgomery County, 2013).

When comparing data between scientific journal publications and non-academic reports, particular distinctions emerge. Hydrological models, like the Soil Water Assessment Tool (SWAT), is more common in scientific literature (Kang and Sridhar, 2018; Renkenberger et al., 2017, 2016; Wagena and Easton, 2018). In contrast, non-academic publications from government, NGOs, or research institutions, are less specific on the future impacts of precipitation changes but they recognize the potential vulnerabilities and emphasize resilience-building approaches (Montgomery County, 2013; Pyke et al., 2008; Williamson et al., 2008).

Some scientific studies show an association between increasing precipitation and human health (Curriero et al., 2001; Liu et al., 2017; Soneja et al., 2016a, 2016b; Urquhart et al., 2014). Soneja et al. (Liu et al., 2017; Soneja et al., 2016a) studies the relationship between changes in precipitation and temperature and increased risk of hospitalization for asthma and water-borne diseases. They show that an increase in the frequency of extreme heat and precipitation events will have a significant impact on public health, especially asthma during summertime extreme precipitation events. It is essential to mention that this association is rare within our sample, and more research in this subject is needed to develop adaptive policies.

The predicted increases in precipitation pose serious management challenges to control nutrient pollution in the Bay and achieve the goals of the *Chesapeake Bay Watershed Agreement* (Chesapeake Bay Program, 2014). Among our sample of documents, data suggests that the water quality in the Bay will undergo biochemical changes that will affect aquatic life. Most notably, the exacerbation of *hypoxia*—

zones of low levels of oxygen that cannot support fish—will have detrimental effects on marine organisms and ecosystems (Boesch, 2008; Du et al., 2018; Harding et al., 2016; Li et al., 2016; Williamson et al., 2008). Although seasonal hypoxia is a natural feature of estuaries, indicators show that these "dead zones" are becoming more frequent in many parts of the world due to human impact on the ecosystem (Pyke et al., 2008; Scavia et al., 2017). Moreover, changes in the water quality and chemistry, as well as higher water temperatures (Glandon et al., 2018; Hines et al., 2010; Pierson et al., 2016) and acidification (Glaspie et al., 2018), pose serious threats to aquatic life. These changes can affect aquatic life that is economically and ecologically important to the Chesapeake Bay; such as the blue crab (Glandon et al., 2018; Hines et al., 2010) softshell clam (Glaspie et al., 2018, 2017), striped bass (IAN Integration and Application Network, 2017), algae (Harding et al., 2016; Williamson et al., 2008), and marine grasses (IAN Integration and Application Network, 2017). The Eco Health Report Card has been a consistent indicator of the Chesapeake Bay's water quality since 1986 (IAN Integration and Application Network, 2017). In 2017, the latest reporting period at the time of this writing, the Eco Health Score was showing a trend of slow improvement. With increasing precipitation and streamflow, it is more likely that maintaining the improvement trend will become harder through this century, and perhaps impossible without aggressive nutrient and pollution reduction management strategies (Boesch, 2008).

2.3.3 EMERGING THEMES IN CLIMATE CHANGE ADAPTATION

Adaptation researchers and professionals may find available studies and reports on data on the projected impacts of more precipitation in the Bay. Conceptually, nothing new is provided by this knowledge. However, societies tend to measure things that matter to them (Pintér et al., 2011). In this case, available data and indicators on aspects of precipitation and their relationship with agricultural productivity, flooding, and water quality are central to increasing resilience. Certainly, more attention is needed on measuring aspects that reduce risk and increase resilience and incorporate those aspects in existing restoration and management efforts. On a qualitative note, multiple types of authors in our sample recognize that there is still much to be done in developing climate adaptation indicators and metrics that can be applied across the Chesapeake Bay watershed in a coordinated fashion to allow for timely implementation of adaptation strategies. The following adaptation themes refer to aspects the authors found to be significant in the development of holistic adaptation measures in the Chesapeake Bay.

Adapting to Sea-Level Rise

Responding and adapting to SLR is a multi-faceted problem. First, improving the quality of data on SLR by upgrading the network of water sensors and real-time flood data will help to predict street-level flooding (Considine and Steinhilber, 2018) better. The development of new datasets can and will facilitate the identification of flood risk areas in coastal communities and support the selection of priority shoreline areas for conservation and/or restoration. Moreover, collaborative decision-driven scientific tools have the potential to support the design of targeted adaptation strategies with known risk-reduction potential (Melissa A Kenney et al., 2016; Melissa A. Kenney et al., 2016).

Developing and deploying the capabilities to identify shoreline areas of significant value and risk-reduction potential becomes relevant at the local level, where county and municipal governments dictate the land-use zoning codes. Empowering county and local-level managers and conservation professionals with tools to identify and monitor coastal habitat changes in real time will likely improve conservation and restoration efforts at the local level. At the state level, managing agencies can facilitate investment for land acquisition programs. In areas where inland migration of wetlands is difficult or impossible, other adaptation options, like green/blue infrastructure, have already been employed. For example, adding sediment to marshes, building oyster reefs, and living shorelines (Johnson, 2010) have positive, albeit limited, benefits (Brock and Beavers, 2015). It may also be useful to promote the evaluation of uncommon adaptation measures and practices (Du et al., 2017).

Adapting to Increases in Precipitation

Overall, the focus of adaptation to projected increases in precipitation relates to (i) the ability to improve our estimates of precipitation patterns into the future and (ii) the ability to upgrade stormwater management systems to meet the projected increase in precipitation. Adapting to precipitation changes will likely reduce flooding, ensure urban water quality, and control and reduce the associated runoff and nutrient loading into the Chesapeake Bay. Many documents reviewed in this report discuss the role of stormwater management as an adaptation focus in the wake of a projected increase of precipitation (Harris and McElfish, 2017; Hoss et al., 2016; Pyke et al., 2008). The stormwater infrastructure that is not intended to handle increased amounts of precipitation will have an increased likelihood of failure (Ambrette, 2017). Communicating the limitations and vulnerabilities of water management systems to local governments will likely encourage the necessary upgrades given the substantial power local government has over stormwater systems management (Grannis et al., 2017; Harris and McElfish, 2017).

Impervious cover due to increasing urbanization prevents stormwater from infiltrating into the soil (Hoss et al., 2016). Therefore, employing green infrastructure and reducing impervious cover in flood-prone areas will increase the ground's capacity to absorb heavy precipitation (City of Baltimore, 2015). Policy changes that encourage resilient building codes and practices are likely to reduce risk, as well as direct new development and investment to less flood-prone areas (Ambrette, 2017). Adaptation-focused documents recommend increasing freeboard standards, the required elevation of the first floors of structures, to account for future SLR and change from a 100-year flood plain management strategy to a 500-year flood plain management strategy (Ambrette, 2017; Considine and Steinhilber, 2018). Upgrading zoning policies in floodplains to incorporate climate risks can both protect existing buildings and strengthen new and substantially improved buildings (City of Baltimore, 2015)(p. 204).

The predicted increase in precipitation in Maryland will result in an increase in agricultural runoff (Segura et al., 2014; Wagena and Easton, 2018), which is likely to forestall progress by management actions without redoubled efforts (Harding et al., 2016). As such, expanding the adoption of best management practices (BMPs) in riparian zones to minimize agricultural runoff, sediment transport, and nutrient loading will become increasingly necessary to address the impacts of climate change related to Bay's water quality. However, it is important for local managers to be able to identify the effectiveness of BMPs. It is recommended that BMPs effectiveness be measured by their GHG-reduction potential; as some research has shown (Gasper et al., 2012). Measuring the performance of BMPs in removing pollutants at different climate scenarios remains an ongoing challenge (Hoss et al., 2016). In the Chesapeake Bay, BMPs are implemented through watershed implementation plans (WIPs), defined by states and districts to ensure the water standard is not compromised. Thus, facilitating knowledge on BMP effectiveness into WIPs would likely accelerate the adoption rates.

Stakeholder Participation

A growing number of documents recognize and recommend the use of collaborative approaches in managing climate adaptation in social-ecological systems (Chesapeake Bay Program, 2015; Grannis et al., 2017; Pyke et al., 2008). Planning for adaptation to SLR and other climate hazard requires regional partnerships and collaborative strategies, especially when climate and environmental hazards transcend municipal and county boundaries (Considine and Steinhilber, 2018). Climate adaptation is an interdisciplinary effort that requires the involvement of actors in social, economic, and environmental aspects of a community and region that bring knowledge pertinent to effective adaptation (Pyke et al., 2008). Measuring the extent to which stakeholder participation delivers measurable improvement and risk-reduction remains a challenge. However, the benefits of collaboration include the ability to create and harmonize data on climate change (e.g., SLR impacts), as it would be difficult for individual communities to collect the data and expertise necessary to address their climate vulnerabilities comprehensively.

Perceptions as Measuring Tools

Finally, a small but distinguishable number of documents focused on measuring perceptions from the public and adaptation professionals related to climate change and impacts. These studies and reports capture different types of perceptions from different types of respondents in different geographic locations. A unifying factor between them is their emphasis on the role perceptions may play in effective coastal climate adaptation planning and implementation. Many documents focused on studying perceptions of risk (i.e., 'feeling at risk of climate impacts') and investigated different variables that may be associated with increasing/reducing risk perceptions among stakeholders (Muter et al., 2013; Prell et al., 2010). Perceptions of climate change may relate to the level of knowledge about climate change, the degree of trust in the responsible agencies, and/or the proximity to climate hazards. Perceptions can function as proxy measures of knowledge and awareness people have about aspects of climate change impacts and adaptation, which may help identify communication gaps among stakeholders (Gore et al., 2009a; Muter et al., 2013). Improving communication between administrators and local residents may greatly increase the effective implementation of adaptation policies. Akerlof et al. (Akerlof et al., 2016b) showed that most residents were uncertain when SLR was going to significantly impact the county. In a survey of residents of Baltimore City and Prince George's County (MD), residents reported a low level of understanding of the climate impacts and their scientific projections (Akerlof et al., 2016a). Having limited knowledge of the facts of climate change has been linked to having a lower perception of risk of climate impacts (Akerlof et al., 2016a). Akerlof (Akerlof et al., 2016b) showed how information-driven collaborative events could have a positive effect on increasing people's awareness of climate risks while aligning their expectations of climate change to that of scientific knowledge. These studies show that such information may have a significant influence on the formation of individual perceptions and public opinion (Kahan, 2015; Leenders, 2002); information that may be helpful in climate change adaptation efforts.

2.3.4 LIMITATIONS

Our review is not without its limitations. First, the impacts discussed in this review are the most dominant and urgent aspects of climate change in the Chesapeake Bay, but they are not the only ones. By accounting for the data/indicators that currently are predominant in the literature we may have neglected important, yet covert, aspects of the social-ecological system that may play silent roles in exacerbating or constraining climate impacts. Second, our review lightly touches on relation between climate changes and human health, which is a subject of interest particularly to state and county governments. Even though we found inconclusive information on this subject we recognize that others have done more focused reviews on this (Hondula et al., 2015). Finally, we recognize that the lengthy process of coding data on the sampled documents is performed by humans who may commit unintended mistakes. To reduce human error, we employed extensive quality control processes, but it is impossible to rule out mis-coding as a possibility.

2.3.5 PRACTICAL IMPLICATIONS

This review article is intended to provide wide-reaching practical implications for tracking climate change impacts and adaptation to those impacts. One of the most important contributions of this review is the description of how climate change data is produced, analyzed, and hosted by different types of authors in different formats. The knowledge network in place in the Chesapeake Bay is complex and includes different stakeholders. Scientists still play an important and growing role in the collection of environmental data, but it is now a noticeable trend how scientists are increasingly diversifying the way in which their studies are communicated to the wider public and policy-makers. More online resources are becoming available, which may present a challenge for local and municipal authorities to identify legitimate and useful sources of science-based information. Taken together, it is possible to say that the web of knowledge on climate change impacts and adaptation is more complex and diverse than it was in 2007, when the Maryland Commission on Climate Change was established. Therefore, reviews like this one are important in assessing the information landscape in a way that may empower stakeholders and decision-makers at all levels of governance to find the right type of information and make informed decisions that support resilience-building and adaptation.

2.4 CONCLUSIONS

Anthropogenic climate change is already affecting the livelihood of humans around the world by driving changes to the ocean and land ecosystems we depend on (Hoegh-Guldberg et al., 2018). As such, governments at different levels (country, state, county, and municipality), academia, and civil society have shown greater interest in tracking the availability and effectiveness of climate change adaptation indicators. The systematic review presented in this article centers in the State of Maryland, USA, home of the Chesapeake Bay, and answered the questions (i) how are indicators of climate impacts measured and reported by different types of authors, document types, and geographic focus? (ii) what are the current approaches for measuring the most pressing climate impacts in Maryland and the Chesapeake Bay? Concerning how climate impacts are measured and reported, we found that most documents in our sample were authored by scientists, followed by state government, NGOs, national, county and municipal governments. The majority of documents were in report form, followed by academic journal articles and online resources. The geographic focus of documents was evenly split with some documents focusing on the State of Maryland and others on the Chesapeake Bay region. A smaller number of documents focused on regional, county, and municipal aspects of climate change adaptation.

We have presented a qualitative and quantitative analysis of the information landscape in this region and have highlighted the synergies that exist between authors researching and working in similar regions and on similar climate-related problems.

For example, how scientists and county managers have shared interests in testing the effectiveness of stormwater management systems in the context of increasing precipitation in the 21th century. At the same time, we have highlighted on some areas where science can meet the needs of practitioners. For example, scientific research can play an important role in identifying shorelines vulnerable to SLR using advance technologies like satellite imagery. As such, the characterization of how quantitative data is produced and reported by different types of authors, document types, and geographic focus is intended to facilitate knowledge exchange between scientists, government, NGOs, and adaptation managers at the county and municipal level in ways that expedite the capacity of adaptation to climate change.

Concerning the current and emerging approaches for the measurement of climate impacts in Maryland and the Chesapeake Bay, we found that most indicators and datasets within our sample are related to SLR and coastal and river flooding. This overwhelming attention to SLR and flooding was not a surprise, given that Maryland’s 4,000-miles of shoreline, and its network of tidal rivers and the Atlantic coast, makes the state particularly susceptible to flooding and erosion brought on by tides, storms, and increasingly SLR. Our review presented some recommendations on areas where emerging scientific research overlaps with government’s interest and communities’ needs. Specifically, we believe that improving real-time data collection of SLR, identifying vulnerable areas, and enabling the state to acquire and/or maintain endangered coastal ecosystems will advance the science and the adaptation to SLR in the region. Changes in precipitation patterns are certain to happen;

however, improving the accuracy of precipitation projections is of utmost importance for those concern about agricultural pollution through runoff into the Bay and the saturation of stormwater management systems in growing urban areas. Furthermore, authorities and the general public are concerned about the efficacy of adaptation measures (e.g., agricultural BMPs, green infrastructure, and socio-economic policies). As such, we identified a growing trend in participatory research being employed as an approach to engage a wider range of stakeholders and solicit information that may lead to better adaptive and collaborative management. These approaches are conducive to the co-creation of knowledge and may achieve the interactions needed between scientists, government, and civil society that may enhance the adaptive capacity to climate change (Lemos et al., 2012). In this respect, we believe that the climate change adaptation community may benefit from knowledge in sustainability science, which overlap in their efforts to understand co-creation of knowledge through transdisciplinary methods (Brandt et al., 2013; Mauser et al., 2013). Moreover, a trend on perception-based research suggests that climate change adaptation performance may be measured, to some extent, by soliciting perceptions of stakeholders about the process and outcomes of collaborative decision-making (Plummer et al., 2017b).

Considering the challenges presented by climate change and the deficiencies of adaptation systems, it is important to develop frameworks and tools that can support climate adaption at different levels of governance. Creating holistic indicators of climate change adaptation is still in early stages of development. Based on our review, we can say that improving the data collection capabilities of environmental changes at different geographic scales and providing collaborative opportunities for stakeholders will likely empower decision-makers and managers with important information. Moreover, social indicators like social capital, stakeholder engagement, and perceptions of risk and awareness are essential for adaptation development and implementation but have not yet evolved into measurable indicators. Even though this review is focused on Maryland and the Chesapeake Bay, we believe these insights can be extend to other coastal areas around the planet that share similar climate-related risks as well as management challenges. Overall, climate adaptation requires the participation of stakeholders and the sharing of information at all geographic and governance levels. This means that experts and practitioners can standardize their engagement with vulnerable local communities and that local communities can increase their exposure to scientific knowledge. It remains a considerable challenge to measure the extent to which scientific knowledge is integrated into local knowledge in a way that translates to effective adaptation management. Nonetheless, we believe that reviews like ours may help stakeholders better understand the complex information network of climate change impacts and adaptation, which in turn may help them navigate it.

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3. A MODEL-DRIVEN APPROACH TO QUANTIFY INDIVIDUAL LEARNING ACROSS MULTIPLE STAKEHOLDER PARTICIPATION NETWORKS

ABSTRACT

Responding to accelerating climate change impacts requires broad and effective engagement with stakeholders, at multiple geographic and governance levels. Stakeholder participation has been hailed as a facilitated approach in climate change adaptation that supports social learning, depolarization of perceptions, and fosters collective action. But stakeholder participation remains loosely interpreted and evaluating measures are limited. This study employs social network analysis (SNA) to investigate how social relations among stakeholders, that emerge as a result of participation, are associated with perceptions of climate change. We hypothesized that reciprocal ties of understanding, respect, and influence can predict perceptions of climate change awareness among stakeholders. This approach was applied to a case study in Deal Island Peninsula, Maryland (USA) where local residents, scientists, and government officials met from 2016 – 2018 to collaboratively manage the impacts of sea-level rise in their communities. We found that social relations based on mutual *understanding*, *respect*, and *influence* are positively associated with changes in perceptions of climate change. We provide a detailed conceptualization and implementation of a network-based approach that may serve as a potential quantitative performance measure of stakeholder participation processes in climate change adaptation. Overall, this study provides empirical evidence of the role that

emerging social relations have on enhancing or constraining social learning among stakeholders in the Deal Island Peninsula project.

3.1 INTRODUCTION

Climate change is increasingly portrayed as a complex, 'wicked' environmental problem (Balint et al., 2011; Markowska et al., 2020). Developing local responses to climate change requires flexible, adaptive strategies based on a holistic understanding of climate change, its drivers and impacts, and the governance structures at varying geographic scales (Pasquier et al., 2020; Teodoro and Nairn, 2020). Stakeholder participation is increasingly seen as a key factor in acquiring a more holistic understanding of complex environmental problems (Baird et al., 2016; Calliari et al., 2019; Pasquier et al., 2020; van Aalst et al., 2008) and developing well-informed local governance responses to climate change impacts (Calliari et al., 2019; Shackleton et al., 2019). Stakeholder participation facilitates knowledge innovations (Cvitanovic et al., 2019; Rathwell et al., 2015), is fundamental for social learning processes (Cundill and Rodela, 2012; Lankester, 2013), and builds social ties among diverse stakeholders (Cockburn et al., 2016; Macgillivray, 2018). Yet evaluating stakeholder participation efforts can be difficult as evaluation frameworks vary across different case studies and research contexts (see Hassenforder et al., 2016). As such, understanding the link between stakeholder participation and its targeted outcomes could be strengthened by frameworks and evaluations that cut across a wide range of cases.

In this paper, we evaluate how stakeholder participation facilitates social learning in climate change adaptation. In constructing our evaluation framework, we draw upon the environmental management (EM) literature pertaining to processes of participation, social networks, and social learning. We apply this framework to a 2.5-year collaborative research project (2016 – 2018) taking place in Chesapeake Bay, USA. Here, researchers from multiple disciplines actively engaged, via a range of workshops and meetings, with community residents and government employees to collaboratively construct a vulnerability-resiliency assessment of the area (Paolisso et al., 2019). Evaluation of the effects this project had on stakeholders' learning and social networks occurred through an online survey, which was administered at the beginning, middle, and end of the project. This survey measured stakeholders' climate change perceptions, as well as a range of social ties to one another. Data gathered from this survey was then compiled and submitted to a network panel linear modeling framework, to assess the extent to which individual stakeholders' perceptions corresponded to the perceptions of others with whom they had social ties. In what follows, we first summarize the literature informing our evaluation framework, and then proceed with a description of our research site, measures, analyses, and results. We conclude with a reflection on how our results link to the larger body of literature on stakeholder participation and social learning, calling attention to the important role played by social networks.

3.2 CONCEPTUAL FRAMEWORK

Our basic premise is that stakeholder participation leads to social interaction and the formation of social ties, and in turn, these interactions and ties lead to social learning on the individual level. By *stakeholder participation*, we mean the process in which all relevant actors engage to discuss a management objective and is guided by a philosophy of empowerment, equity, trust, and learning (Anggraeni et al., 2019; Reed, 2008). This participatory process aims to systematize knowledge in a way that is useful to practitioners and scientists (Schwilch et al., 2012). *Social ties* refer to the relations linking individuals together and can range from those based on social interaction to relations based on respect and understanding. Finally, *social learning* refers to an individual's change in perceptions or beliefs as a result of being exposed to the perceptions or beliefs of others within a participatory group (van der Wal et al., 2014). In what follows, we summarize the literature linking these processes together.

3.2.1 PARTICIPATION AND SOCIAL NETWORKS

Environmental management studies indicate that engaging stakeholders in participatory processes provide unique opportunities for stakeholders to interact face-to-face and share their views (Daniels and Walker, 2001; Lumosi et al., 2019; Paolisso et al., 2019). Such interactions form channels through which information can flow (Ernoul and Wardell-Johnson, 2013), and mutual understanding to occur (Rist et al., 2006). In addition, these interactions can lead to the formation of collaboration ties (Anggraeni et al., 2019; Baird et al., 2018; Bodin and Crona, 2009; Kochskämper et al., 2016; Masuda, 2007), and ties based on trust and/or respect (Cundill and

Rodela, 2012; García-Nieto et al., 2019). The field of social network analysis (SNA) has increasingly been adopted within the EM field as a means for capturing such relations (Bodin, 2017; Bodin and Prell, 2011). The application of network analysis has tested the extent to which participation leads to tie formation among stakeholders (Baird et al., 2016; Plummer et al., 2017a), as well as a means for identifying diverse stakeholders in participatory processes (Prell et al., 2011).

3.2.2 PARTICIPATION AND LEARNING

EM research adopting an SNA approach also indicates that social networks act as moderating mechanisms that lead to stakeholder learning (Cundill and Rodela, 2012; Lankester, 2013; Schwilch et al., 2012). Here, social ties are seen as conduits for explicit and implicit information flows regarding environmental problems and management issues (Sandström et al., 2014), which exposes stakeholders to the perceptions and beliefs of others and may lead them to modify their views and/or behaviors regarding an environmental issue (Crona et al., 2011; Muter et al., 2013). Such a process of linking, sharing information, and modifying one's views and/or behavior is referred to as social contagion (Burt, 1987). Leenders (2002) operationalized social contagion as a result of an individual's embeddedness in a social network, where *embeddedness* refers to the degree to which an individual is linked to others within a bounded set network of actors (e.g., participatory workshops). As the level of embeddedness increases for an individual, so is the likelihood of that person changing his/her views based on the views of networked partners, thus enabling the process of social contagion to occur (Burt, 1987; Doreian et al., 1989; Leenders, 2002).

Studies across a range of empirical contexts have given support for social contagion (e.g., Christakis and Fowler, 2013; Friedkin, 2001; Marsden and Friedkin, 1993). In the context of EM, Muter et al. (2013) found evidence for contagion happening between experts and laypeople regarding their perceptions of wildlife conservation. In particular, they found that having more/stronger communication ties between experts and laypeople made them more likely to share similar perceptions about wildlife management. Prell et al. (2010) and de Nooy (2013) found similar results when evaluating how stakeholders share similar knowledge, values, and perceptions with communication partners. However, not all types of knowledge, values, and perceptions have the same degree of contagion, as individuals may seek only certain types of information from their networked partners but not others (de Nooy, 2013). Similarly, Matous and Todo (2015) found that information-exchange ties among farmers led to the diffusion of composting practices in Ethiopia. As such, social networks can lead to more than the contagion of knowledge and perceptions, it may lead to behavioral changes in environmental management (Matous and Todo, 2015).

Social contagion can occur via *different* types of social networks, but not necessarily in *all* kinds of networks. In other words, some networks may not be best suited for contagion processes of certain perceptions. For example, Muter et al. (2013) showed that some perceptions were not associated with communication ties but did not discard the possibility that actors may have been influenced by other, unobserved, networks. As such, studies that only consider one social network, such as communication (de Nooy, 2013; Prell et al., 2010), collaboration ties (Bodin, 2017;

de Klepper et al., 2010), and/or advice (Freitag et al., 2018; Gibbons, 2004; Matous and Todo, 2015), may only provide partial views of social contagion within the scope of a single network. Gathering data on multiple networks may enable a study to better capture the variety of social processes linking stakeholders together (Hauck et al., 2016; Therrien et al., 2018). Thus, providing a deeper, more nuanced understanding of the dimensionality of the social processes influencing perceptions and behavior.

In this study, we present a quantitative SNA approach that captures specific relational networks among stakeholders arising out of the participatory process. These ties are based on understanding, respect, and influence. Ties based on understanding are those in which actors believe other actors in the network understand their views, beliefs, or values. Such ties are expected to increase among stakeholders as a result of participatory practices (Lumosi et al., 2019; Mostert et al., 2007; Reed et al., 2010; Rist et al., 2006; Schwilch et al., 2012). Similarly, ties based on respect are those in which stakeholders feel that other participants respect their views, beliefs, and values, and again, the participation literature notes the importance of maintaining and strengthening respect among stakeholders via the participatory process (Kocho-Schellenberg and Berkes, 2015; Rathwell et al., 2015; Rist et al., 2006). Finally, ties based on influence are those in which stakeholders feel that other participants have influenced their views, beliefs, and values. The literature refers to influence in participation as the relative power some individuals have to influence others (Ceddia et al., 2017; Hauck et al., 2016, 2015; Schiffer and Hauck, 2010). Collectively, this range of networks aims to capture the multidimensionality of relationships that arise among stakeholders via participation, and then tests the extent to which these relations (individually or collectively) lead to contagion. Yet in addition, we also capture the varying strength of ties for each relation. Tie strength refers to the degree of emotional intensity, intimacy, and reciprocity of a social tie between two actors (Krackhardt et al., 2003), and may be captured through a Likert scale item. In the literature, stronger ties are often linked to stakeholder influence and mutual learning (Prell et al., 2009), while weaker ties are linked to access to new information (Granovetter, 1983). For contagion processes, stronger ties between two actors in a network increase the likelihood of both adopting similar views and behaviors (Muter et al., 2013).

Taken together, the evaluative approach presented here advances the work linking social networks to EM outcomes in a number of key respects. First, we capture greater complexity by measuring a range of networks, over time, among the same set of actors. These networks, moreover, also capture the varying strength of ties linking actors together. As such, by quantitatively measuring network multiplexity and varying tie strength, over time, we bring a level of precision to EM studies that aim to capture complex social processes and their outcomes. Second, we measure the impact that stakeholder networks, formed through participatory processes, have on individual learning by linking these two via a contagion approach that directly accounts for stakeholders' ties and the perceptions of networked partners. In this way, our approach advances the measurement of learning from perception-based measures to one that accounts for the role of social relations. Finally, this approach is embedded within a transdisciplinary research project, where scientists engaged directly as part of the research project, in this way, this knowledge can be facilitated to practitioners and other stakeholders that may employ a similar approach in different regions.

3.3 MATERIALS AND METHODS

3.2.1 STUDY AREA

To address the aim of this study, we selected a case study with the participatory conditions needed to test our methodology. The Deal Island peninsula is located on the Eastern Shore of Maryland, USA, along the Chesapeake Bay. The peninsula covers an area of approximately 18 square miles, inhabited by about 1000 people. Given the ideal location at the shore, the main source of income is from harvesting seafood, mainly crabs (*Calliencecus sapidus*) and oysters (*Crassostrea virginica*), and many of the inhabitants' families have lived similar lifestyles on this island for many generations over the last 300 years. The island is experiencing an increase in flooding and coastal erosion related to a changing climate (Paolisso et al., 2019). Projections of future climate change in the Chesapeake Bay show, among others, an increase in sea-level rise, storm frequency and severity, flooding, and erosion (Teodoro and Nairn, 2020). Recent changes in demographics have led to an increase in difficulty for the local people to organize themselves and address the problems arising from the sea-level rise (Paolisso et al., 2019). As a result, a network of stakeholders including scientists, local and state government representatives, and residents have established the Deal Island Peninsula Project (DIPP), which aims to reduce the vulnerabilities of the Deal Island Peninsula area to the climate impacts by creating partnerships between communities and relevant stakeholders through a collaborative science and learning approach (Miller Hesed et al., 2020). We chose this area because of DIPP's focus on climate adaptation and its goal to facilitate learning across a diverse set of stakeholders.

3.3.2 DATA COLLECTION AND DATA CHARACTERISTICS

Online surveys were distributed to active participants of DIPP as part of the Integrative Coastal Resiliency Assessment (ICRA), which collected data three times between 2016 –2018. The survey was divided into two main components: a part of the perceptions of climate change and another part of the social ties between stakeholders. The questions on perceptions included seven 4-point Likert statements on climate change (Table 1). Participants were asked to rate the statements depending on how much they agreed or disagreed with each statement. Individual statements were intended to gauge the perceptions of the respondent on climate change awareness, risks, and actions. The responses had high internal reliability (Cronbach α = 0.96) and were combined into a single averaged score. This score can be interpreted as a person's overall level of awareness of the causes and impacts of climate change in their community.

Table 1: Questions for measuring perceptions of climate change in the survey

1. The climate is changing in different ways from before due to the impacts of human activities.
2. Climate change is affecting the communities of the Deal Island Peninsula already.
3. Climate change is affecting the environment of the Deal Island Peninsula already.
4. The Deal Island Peninsula area will experience more storms and floods in the future due to climate change.
5. The resilience of Deal Island Peninsula communities will be reduced in the future due to climate change.
6. Climate change is a significant threat to the social and ecological system of the Deal Island Peninsula.
7. Building relationships with people and organizations that have an interest in the Deal Island Peninsula and can help communities cope with climate change.

On the social networks section of the survey, participants were asked to provide information about four types of social relations they held with other participants in the DIPP (Table 2). A roster was provided to each respondent with the names of all other DIPP members, and respondents were asked three Likert scaled network questions (where 1 = ‘a little’, 2 = ‘somewhat’, 3 = ‘a lot’, 0 = non-existent) pertaining to perceived feelings of understanding, respect, and influence (see Table 2). These three network measures were included to gauge how feelings of respect, understanding, and influence changed over time as a result of DIPP participation. However, as some participants had more face-to-face interaction outside of DIPP meetings than others (e.g. they were neighbors or worked at the same organization), we also included this interaction network as a control measure to take into account the extent to which stakeholders interacted with others outside of the DIPP (see question 4, Table 2).

Table 2: Social relations data and corresponding survey questions

Type of network	Network question in the survey
1. Understanding	This person understands my views regarding the DIPP area.
2. Respect	I feel this person respects my views/ beliefs regarding the community and environmental problems facing Deal Island.
3. Influence	This person has influenced my understanding of the community and environmental problems affecting the DIPP area.
4. Interaction	Do you interact with this person outside the project?

Additional control data collected via the survey included age, gender, income level, and stakeholder category (i.e., whether a person was a local, a government official, or a scientist; see Table 3). By including the stakeholder category as a dummy variable, we were able to isolate the network effects within stakeholder categories.

Table 3: Longitudinal qualities of collected data

	T = 1 (N = 53)	**T = 2 (N = 52)**	**T = 3 (N = 42)**
Stakeholder Type			
Local	19	19	19
Scientists	13	12	8
Government	21	20	14
Age			
Mean	42.21	52.77	52.83
Min	29	29	29
Max	79	79	75
Gender			
Male	31	28	22
Female	22	24	20
Income (1 – 9)			
Mean	4.51	5.81	5.80

3.3.3 OPERATIONALIZING SOCIAL CONTAGION

Social ties are commonly represented in SNA as a square matrix (W), where all stakeholders sending ties are represented in rows (W_i) and stakeholders receiving ties are represented in columns (W_j). The tie value between any pair of stakeholders is represented in matrix W as nonzero W_{ij} values.

Although most network studies focus on binary networks, modeling empirical networks in which the strength or intensity of tie varies could provide greater insights into the social system under question, and a richer understanding of the social relationships overall (Barrat et al., 2004). In our dataset, although we captured ties ranging from weak, i.e. where respondents gave their relationship with another participant a ranking of 1 (‘little’), to moderate, i.e. with a ranking of 2 (‘sometimes’), and strong, i.e. where respondents ranked the strength of a tie as 3 ('a lot'), for modeling purposes, we discarded all weak ties from the dataset, and only included those ties with a rank of moderate ('sometimes') or strong ('a lot'). This decision to discard weak ties was based on the fact that i) past SNA research has shown, across an array of empirical contexts, that stronger ties are good in the implementation of conservation and adaptation actions (Barnes et al., 2017; Bodin et al., 2019; Weenig and Midden, 1991), and ii) stronger ties are better predictors of similarities in views among stakeholders because a person is more likely to adopt the views of someone they trust and share a degree of intimacy (Prell et al., 2010). The strength of a tie may affect the perceptions of actors in different ways depending on the number of ties a given actor holds with others and the perceptions of those others (Figure 5).

In addition to discarding weak ties from our dataset, we also discarded non-reciprocated links, following Krackhardt et al. (2003). The decision for focusing on reciprocal ties was founded, firstly, on the emphasis placed in participatory literature, and on the importance of *mutual* learning in participation (Bhattachan et al., 2018). This means that the exchange of knowledge among stakeholders is expected to be a two-way exchange based on understanding, respect, and/or influence (Bhattachan et al., 2018; Rathwell et al., 2015; Rist et al., 2006).

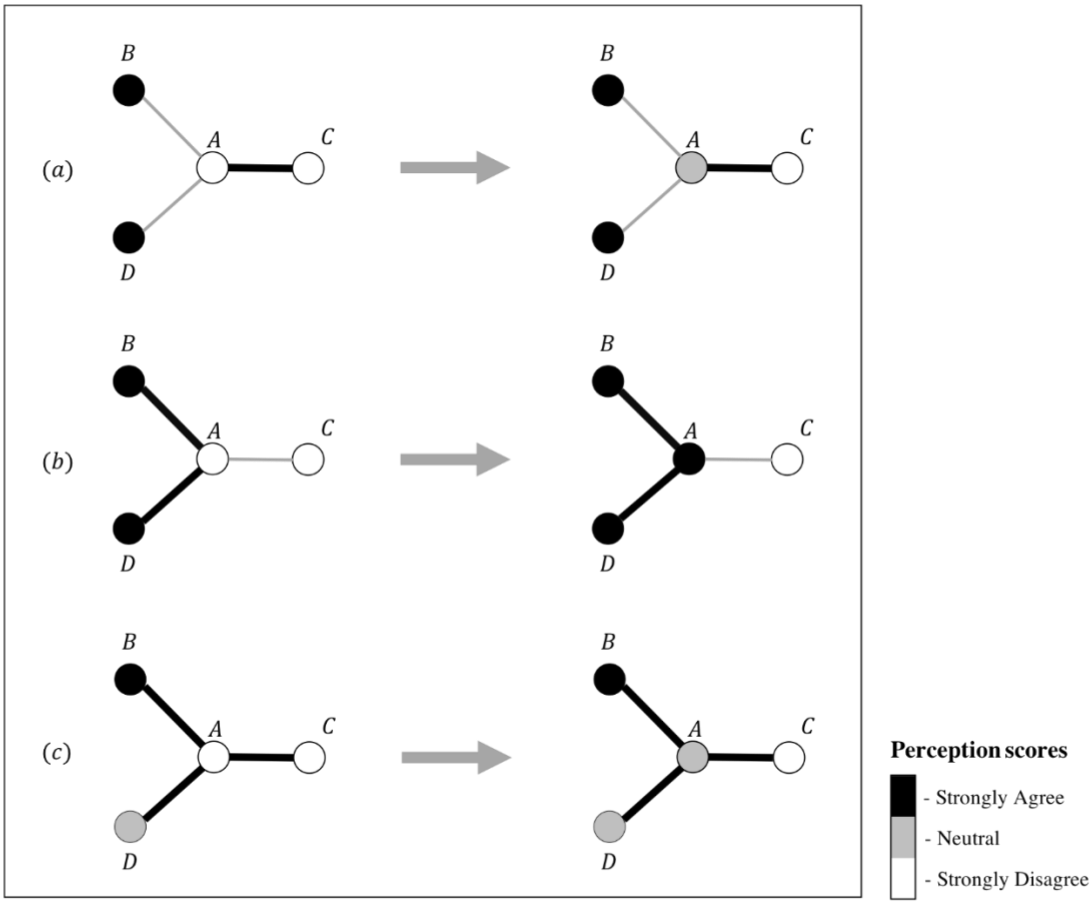

Figure 5: Different settings where strong ties may impact perceptions over time: (a) a strong tie may counteract influence from others, (b) strong ties with actors with drastically different views may accelerate a rapid change in perceptions, (c) strong ties with actors with varying degrees of perceptions may lead to a moderate change in perceptions.

Our resulting matrix thus consisted of valued, reciprocal ties among stakeholders, where a 1 = moderate, and 2 = strong ties. Additionally, following suggestions of Leenders (2002), we normalized W by row, which transforms the network ties into weights distributed to all of the ego's outgoing ties and whose sum equals 1 for all stakeholders. The row-normalization is applicable when the goal is to limit the incoming influence for all stakeholders. However, by doing this we do not consider the influence people exert on others. This approach was used because of our focus on individual learning. Using this transformed W matrix, we can then operationalize influence using the following formula:

(1) $$A_{rt} = W_{rt} y_t$$

Where A_{rt} contain the variables of influence for each social relation (*r*) in period *t*, W_{rt} are distinct network weighted matrices (four in our case) in period *t*, and y is the vector of perception scores of climate change awareness for all stakeholders in period *t*. This multiplication generated a vector of weighted sums of perceptions to which each stakeholder was exposed. After computing the influence variables (A_{rt}) we introduced it to a network panel linear model (formula 2) to evaluate the effect each network (*r*) has on climate change perception scores:[1]

(2) $$y_{it} = \beta_1 A_{rt} + \beta_2 x_{it} + a_i + \varepsilon_{it}$$

where *i* = 1, ..., n is the individual stakeholder index, *t* = 1, …, *T* is the time index, a_i is the individual unobserved effect, and ε_{it} a random disturbance term of mean 0. We assume that the unobserved effect a_i is uncorrelated with the explanatory variables (independent of all explanatory variables in all periods) and we consider the network as non-random and exogenous, following Jochmans and Wiedner (2019). The analysis was done using the *plm* routine in R package *plm* (Croissant and Millo, 2008). This approach was adequate to deal with changes in the sample size at every

1 This model is akin to network autocorrelation models (Doreian, 1989; Leenders, 2002) for longitudinal data.

data collection period, which is an important consideration and challenge for researchers studying stakeholder participation processes over time.

Part of our contribution is the unpacking and testing of different social ties that may predict perception changes among stakeholders. If the perceptions at three time periods are statistically associated with network changes, then we may infer that learning through social contagion was occurring. The effect that each network has on predicting perceptions of climate change may be considered independently, although a combined analysis can be made to compare the relative effect each network has on perceptions.

3.4 RESULTS

In this section, we first present the descriptive results for each social network and the corresponding variable of influence. Then, we present the modeling results for each social network as well as the results of a combined model.

3.4.1 DESCRIPTIVE NETWORK-LEVEL DATA

Descriptive measures were computed to characterize the structure of our social relationships (Table 4). Summary statistics of each network include (1) the density, which refers to the size and level of connectivity in a network (i.e., the ratio of existing ties and the number of all possible ties); (2) the average degree centrality, which is the average number of reciprocal ties for all stakeholders at any given time; (3) its centralization, which indicates the level of hierarchy present in the network; and (4) the number of total ties in each network. These measures are qualitative indicators of social connectivity and provide information on the network dataset used in this analysis.

Table 4: Summary of reciprocal network-level descriptive statistics

Networks	Waves	Ave. Centrality (SD)	Centralization	Density	Total ties
Understand					
	Wave 1:	2.98 (3.35)	0.367	0.057	158
	Wave 2:	3.85 (4.02)	0.370	0.075	200
	Wave 3:	6.00 (5.72)	0.613	0.146	252
Respect					
	Wave 1:	3.17 (3.70)	0.529	0.061	168
	Wave 2:	4.31 (4.32)	0.406	0.084	224
	Wave 3:	6.09 (5.74)	0.743	0.148	256
Influence					
	Wave 1:	2.19 (2.99)	0.409	0.042	116
	Wave 2:	2.19 (3.21)	0.292	0.043	114
	Wave 3:	3.62 (4.32)	0.487	0.088	152
Interaction					
	Wave 1:	2.38 (2.33)	0.138	0.048	126
	Wave 2:	3.08 (2.71)	0.241	0.060	160
	Wave 3:	2.95 (2.65)	0.254	0.072	124

Looking solely at the structural characteristics of the social network (Table 4), we observed the following: both the *Understanding* and *Respect* networks follow similar trends over time. Their sizes grew in similar proportions as shown by their densities and number of ties. Their average degree jumps to 6.00 and 6.09 at period 3 for *Understanding* and *Respect* networks, respectively; making these networks the ones with the most connectivity increase in our data sample. Moreover, the centralization score for *Understanding* and *Respect* networks are roughly similar which suggests that these networks become highly centralized by period 3, compared to all other networks. The *Influence* network significantly increased in size and connectivity during period 3 but its centralization score remained roughly consistent. The *Interaction* network shows a steady composition throughout the three periods. Its size, centrality, and centralization remain roughly consistent. Its lower centralization score compared to other networks suggests informal interaction ties are spread out among stakeholders and that there is no central group of actors that everybody interacts with outside the project. A low centralization score shows that the DIPP network is diverse.

Perceptions of climate change are mostly within the upper side of the scale—most actors hold climate change perception scores between 3 and 4 (4 = “strongly agree”). The generally high level of climate change perceptions in our dataset was expected, given that most stakeholders in DIPP had been meeting and collaborating for a few years before the ICRA data was collected. A visualization of the level of climate change perceptions to which stakeholders were exposed is shown in Figure 6.

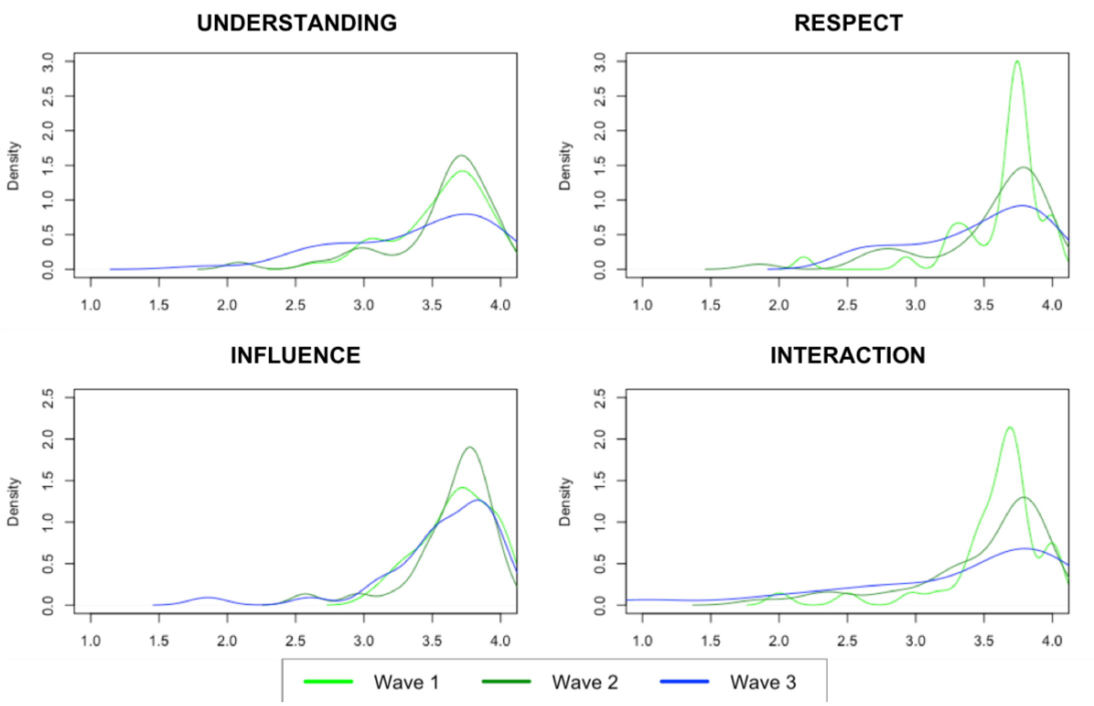

Figure 6: Density plots of overall perceptions of climate awareness to which stakeholders are exposed to divided by data periods.

The majority of respondents (60%) in our sample were exposed to high levels of climate change perceptions. This pattern is true for all networks at all periods, with some important nuances. First, the *Understanding* network shows a decreasing trend in the proportion of people exposed to high levels of climate change perceptions, from 67.8% in period 1 to 61.9% in period 3. A decreasing value may be seen as a positive outcome, given that more *Understanding* ties may have been formed between stakeholders with initially different views on climate change (e.g., scientists reporting they felt understood by locals). On the other hand, the *Respect* and *Influence* networks show an increase in the proportion of people exposed to high levels of climate change perceptions from period 1 (66% and 60%) to period 3 (69% and 70%), respectively. An interpretation of this may be that more people reported being respected and influenced by individuals who reported high scores of climate change perceptions (e.g., locals increasingly reporting they felt respected and influenced by scientists). The network of outside-project interaction shows some variability in the proportion of stakeholders influenced by high levels of climate change perceptions, but with no recognizable trend.

3.4.2 PANEL MODEL RESULTS

The results of models (1) – (10) in .

Table 5 show that the individual social networks based on reciprocal understanding, respect, influence, and interaction outside of the project, predict a statistically significant and positive relationship with the levels of climate change perceptions among stakeholders. When looking at the effects of control variables (age, gender, income), we see that age is consistently significant in the full model of all networks. Age's negative coefficient suggests that older respondents are more likely to have lower climate change perception scores when controlling for all other effects and social networks. In the literature, the relationship between age and perceptions of climate change is inconclusive, with some finding a positive relationship (Apata et al., 2009) and others a negative (Aphunu and Nwabeze, 2013). Here, we show that age is indeed a significant predictor of climate change perceptions, with a negative relationship. Income is significant in the *Influence* network, suggesting that individuals with high income are more likely to have higher levels of climate change perceptions.

When looking at stakeholder characteristics (i.e., stakeholder type), belonging to a local resident category was only significant in the base models but became insignificant in the full models for all networks. The dummy variable for data period 3 (*t3*) was significant in the *Understanding* and *Respect* networks; suggesting that on that period of data collection, a significant number of understanding and respect ties were created that facilitated the influence of perceptions of climate change.

Model (11) in .

Table 5 indicates that when modeled jointly, although all social network effects are positive, only the reciprocal networks of *Influence* and *Interaction* have a significant association with climate change perceptions. This may be because stakeholders can aptly identify those others that have influenced them the most, and thus the relation between influence ties and actual influence in perceptions are stronger than those of understanding and respect and thus crowding out the effects of understanding and respect ties. It is important to emphasize that influence ties are reciprocal, meaning that both the sender and receiver acknowledge each other as influential.

Table 5: Social network effects show a significant relationship with climate change perceptions in network panel modeling frameworks with prominent control variables.

	Predicting: Perceptions of Climate Change										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Social networks effects:											
Understanding	0.484***	0.448***	0.491***								0.297
	(0.105)	(0.102)	(0.104)								(0.242)
Respect				0.514***	0.493***	0.540***					0.036
				(0.125)	(0.121)	(0.123)					(0.276)
Influence							0.358***	0.415***	0.424***		0.228*
							(0.133)	(0.129)	(0.128)		(0.135)
Interaction										0.436***	0.337**
										(0.090)	(0.170)
Control variables:											
Research	0.029	0.190	0.179	0.047	0.191	0.187	0.099	0.280	0.273	0.251	
	(0.171)	(0.172)	(0.173)	(0.170)	(0.167)	(0.168)	(0.219)	(0.205)	(0.208)	(0.169)	
Local	-0.616***	-0.289	-0.305	-0.569***	-0.259	-0.255	-0.792***	-0.356	-0.366	-0.125	
	(0.194)	(0.209)	(0.209)	(0.192)	(0.205)	(0.205)	(0.239)	(0.241)	(0.244)	(0.209)	
Age		-0.011**	-0.011**		-0.010**	-0.011**		-0.013***	-0.014***	-0.014***	
		(0.004)	(0.005)		(0.004)	(0.004)		(0.005)	(0.005)	(0.005)	
Gender		-0.165	-0.141		-0.212	-0.188		-0.209	-0.198	-0.122	
		(0.155)	(0.156)		(0.146)	(0.147)		(0.183)	(0.185)	(0.148)	
Income		0.040	0.034		0.032	0.028		0.066**	0.063*	0.011	
		(0.029)	(0.029)		(0.028)	(0.029)		(0.033)	(0.033)	(0.029)	
t2			0.068			0.087			0.104	0.062	
			(0.067)			(0.069)			(0.077)	(0.059)	
t3			0.151**			0.137*			0.101	0.091	
			(0.074)			(0.074)			(0.081)	(0.067)	
Constant	1.849***	2.271***	2.094***	1.737***	2.150***	1.958***	2.195***	2.291***	2.245***	2.598***	0.252
	(0.402)	(0.445)	(0.452)	(0.473)	(0.497)	(0.508)	(0.516)	(0.575)	(0.575)	(0.405)	(0.659)
Observations	112	111	111	115	114	114	92	91	91	110	84
R^2	0.391	0.447	0.466	0.382	0.447	0.463	0.314	0.416	0.427	0.494	0.399
Adjusted R^2	0.374	0.415	0.425	0.366	0.416	0.422	0.291	0.375	0.371	0.454	0.369
AIC	31.85	27.54	24.37	34.39	32.82	31.07	23.99	23.12	21.59	-4.14	15.452
F Statistic	64.192***	80.145***	85.077***	65.764***	84.017***	87.887***	33.868***	54.740***	56.266***	97.937***	48.877***

*p<0.1; **p<0.05; ***p<0.01

3.5 DISCUSSION

The goal of this study was to investigate the effect that social networks have on social learning, which we defined as a change in perceptions in stakeholder participation. Specifically, we constructed a variable to measure social contagion which accounted for the number and strength of social ties that each stakeholder established during a participatory process. This paper focused on multiple, valued social networks that are believed to be important aspects of stakeholder participation. Results show that reciprocal networks of *Understanding*, *Respect*, *Influence*, and *Interaction* have a statistically significant and positive relationship with perceptions of climate change in the DIPP case study. Thus, stakeholders in our study aligned their climate change views with those of their networked partners, across a range of social relations. These results provide implications for researchers and practitioners in climate change adaptation: namely in the management of stakeholder engagement processes. The methodological approach presented in this study may be replicated elsewhere to expand our findings and as an evaluation tool. Stakeholder participation is costly and time-consuming, and achieving its desired outcomes requires long-term commitments from all parties involved. However, our study shows that networks can capture social dynamics associated with learning even in 2.5 years.

The understanding network seems to be a reliable predictor of climate change perceptions among DIPP stakeholders. Asking individuals if they felt understood by other participants involves asking them about their experience within the participatory process, which goes beyond a simple connection. Indeed, feeling understood is a sign that, regardless of stakeholder type, individuals care about being able to express themselves and feeling like others acknowledge their views and understand them (Lauer et al., 2017). Reciprocal ties of understanding translate to mutual-understanding, which has shown to be a viable social dynamics that facilitate learning (Lumosi et al., 2019). Similarly, our results show that feeling respected by and respecting other individuals are also social processes that support learning in stakeholder participation. In the case of the DIPP stakeholders, feeling understood and respected showed similar results. Certainly, one could argue that both mutual-understanding and mutual-respect contribute to an inclusive atmosphere in heterogeneous participatory projects (de Vente et al., 2016). Moreover, mutual-influence in the joint model (11) showed a statistically significant and stronger effect than that of understanding and respect ties, which suggests that asking stakeholders to identify those who had influenced their understanding of the community and environmental problems in the DIPP area is a direct and meaningful approach to map how the contagion of perceptions spreads through a network. Mutual-influence ties between individuals who have different, often opposing, views suggest that participatory processes like DIPP can facilitate the formation of influential ties, those that support learning, among individuals that have different backgrounds and professions. For example, scientists and coastal residents may both be influenced by each other. Scientists may learn about the local priorities and challenges directly from local residents who, in turn, may become more open to scientific information if they feel respected and understood by scientists. As a result, both may be open to learning from each other.

In our study, we used an *Interaction* network (interaction outside the project) as a control to distinguish the social processes that influence perception-formation outside the DIPP process. The fact that the *Interaction* network was significant echoes previous studies that had considered the role of communication and interaction ties on actors' environmental perceptions (Gore et al., 2009b; Jasny et al., 2015; Prell et al., 2010; Scherer and Cho, 2003). As such, our selection of social networks seems to expand the understanding of relational aspects, other than communication and interaction, that are associated with the contagion on perceptions.

This study's findings suggest that a participatory process that nurtures an atmosphere where stakeholders increasingly feel understood, respected, and open to the influence of others is conducive for learning. The fact that all networks show significance in predicting perceptions of climate change show that these social aspects can, and should, be measured in stakeholder participation. Several scholars have argued that the quality of outcomes depends greatly on the quality of the participatory process (de Vente et al., 2016; Plummer et al., 2017b). Our findings provide multiple networks-based evidence that the process is indeed important at predicting learning as an outcome. Networks of understanding, respect, and influence grew as the participatory process evolved, which highlights the positive impact that stakeholder engagement can have in developing larger, stronger, and diverse networks that may increase the adaptive capacity of a community to climate changes (Anggraeni et al., 2019; Cundill and Rodela, 2012).

Our results show that the level of climate change awareness is the highest in the scientist group, moderately lower in the government official group, and the lowest in the local resident group, although the difference is not significant among the first two groups and is not statistically robust among the first and third group. This may be attributed to the limited number of categories stakeholders could belong to. If a greater distinction would have been made between different levels of government, for example, or the inclusion of additional stakeholder sub-groups (e.g., local residents and seasonal residents, or municipal government and state government), then perhaps a better understanding of the inter-group differences may have been possible. However, previous research has also shown that perceptions of environmental issues are not necessarily correlated to the stakeholder group or institutional affiliation (Prell et al., 2010). In which case our findings may support the notion that social ties are stronger predictors of perception diversity than stakeholder categories.

We have presented a model-driven approach as a viable means of capturing social learning within stakeholder participation. This approach draws from a long tradition of network autocorrelation models that used valued network data and assigns weights to the ties each stakeholder hold (e.g., Dekker et al., 2007). Depending on the weight of each tie, the more influence those ties have on a stakeholder. This means that if an individual feels strongly understood, respected, or influenced by another person, as opposed to just moderately understood, respected, or influenced that individual is more likely to resemble the views and perception of those individuals with whom they hold stronger ties. Our approach provides an important contribution of valued network data in stakeholder participation research, which has been dominated by the use of binary networks. We have shown that the strength of ties is a relevant consideration when measuring learning among stakeholders. The approach presented here can be applied in different cases and contexts where learning is the desired outcome in participatory processes. We suggest that this framework is more appropriate in stakeholder participation projects where network data collection is accessible. Our measure of social contagion directly links learning to social ties that are established or strengthened during participation. In this way, we separate ourselves from common measures, such as Plummer et al. (2017a), which only include self-reported learning and participatory process variables. Our measure is more accurate in capturing the social dimensions within participatory processes.

This study has important implications for policy-making and management of climate change adaptation. Stakeholder participation is becoming commonplace in climate change adaptation and environmental governance (García-Nieto et al., 2019; Reed, 2008). However, the implementation of these processes is dependent on financial and human resources from funding agencies. In the case of the Deal Island Peninsula project, funding came from the Maryland Sea Grant (MDSG), a state-level research institution that supports participatory science and science-based policy-making. Funding institutions need to justify their investment and provide supporting evidence of the outcomes of participatory projects. We believe that this study enables both researchers and practitioners to think of new ways of measuring social outcomes of participation, like learning. Participatory processes, in effect, are akin to negotiations that lead to outcomes. If so, then providing a measure of understanding and respect in relation to social learning within stakeholder deliberations may provide valuable insight into the decision-making process.

The results from this study were shared with key MDSG personnel and NGO organizations involved in climate change adaptation in the Chesapeake Bay, following transdisciplinary approaches of participatory research (e.g., Mauser et al., 2013; Schmidt et al., 2014). The authors received positive feedback from the presentation of findings and the authors perceived adaptation practitioners and funding agents were satisfied to see evidence that stakeholder participation leads to desired outcomes. Policy-makers and climate adaptation practitioners increasingly need more data on stakeholder participation to procure and channel funding with informed expectations of its success.

This study is not without its limitations and an important one to mention is that we did not evaluate the process and extent to which participation leads to tie formation. Active participation can be measured by considering the instances where stakeholders were present in participatory events, i.e., the number of times they met throughout the course of the study. Our study did not consider how co-attendance by two stakeholders would lead to tie formation between them, this is something future research may consider. Our measure of social contagion provides a useful way of generating valued network data. However, our analysis may not have captured a wide enough range of tie strengths, as we only considered two degrees of tie strength (i.e., moderate and strong). As such, future work can extend the range of tie strength to more detailed levels and test whether social ties have a spectrum of closeness and the extent to which it matters when testing for social contagion of perceptions. Moreover, the process and the results of this study do not point concretely on the dynamic interaction between the ties and the perception change. In other words, we cannot assert whether (i) establishing more mutual-understanding ties raises climate change perception scores, or if (ii) individuals with high climate change perception scores establish ties with others that share similar perceptions. To answer these questions between competing hypotheses of social contagion (Burt, 1987; Leenders, 2002) and social selection (McPherson et al., 2001) requires the use of more complicated statistical analyses that can simultaneously test both hypotheses (Stadtfeld et al., 2018).

In this study, stakeholder participation partly emerged from pre-existing social ties among DIPP participants and was partly driven by individuals' decision to participate after becoming aware of the project's existence. It would be relevant to employ this measure in a participatory context at an earlier stage of engagement, where stakeholders do not have pre-existing social contact and test the time it takes for social learning to be picked up by an evaluation framework such as ours. Future research can improve the understanding of social contagion through ties of mutual understanding and respect by testing their predictive power on other types of perceptions (e.g., perceptions of resilience, adaptive capacity, or vulnerability). Also, collecting network and perception data for a longer period may provide insights into the strength of this relationship in longer periods.

Overall, we can interpret these results in the following way: stakeholders that share bonds of mutual-understanding, mutual-respect, and mutual-influence with other stakeholders that have a high level of climate change perceptions are more likely to have a high level of climate change perceptions themselves. The degree to which these networks support the transfer of perceptions (i.e., social learning) can be measured, as we have done in this study, by directly linking changes in perceptions to properties of the collaborative process, namely the set of emerging social networks between stakeholders. As a result of this knowledge, we can assume that a participatory process that fosters mutual understanding, respect, and influence among participants that have varying levels of climate change perceptions, is likely to increase the levels of climate change awareness overall. We limit our interpretation of the results to the DIPP stakeholder network. The implementation of stakeholder participation mechanisms is to a large extent locally-bound and addresses local problems with the involvement of locally-relevant individuals. As such, we cannot generalize our findings to all processes that bring about shared understanding and social influence. Notwithstanding, this study demonstrates a generalizable model-driven approach for quantifying individual learning across multiple stakeholder participation networks and enriches a growing empirical literature of social contagion and social learning, to which our study adds support for processes of social learning in stakeholder participation in the context of climate change adaptation.

3.6 CONCLUSION

Responding to accelerating climate change impacts requires broad and effective engagement with stakeholders, at multiple geographic and governance levels. In this study, we tested the relationship that exists between social ties among stakeholders in a participatory process and changes of climate change perceptions (i.e., learning). Our findings suggest that social learning can be partially explained by social ties that are established and nurtured within participatory processes. Specifically, reciprocal ties based on understanding, respect, and influence capture important processes and outcomes characteristic of stakeholder participation. These findings showcase novel mediums on which contagion of perceptions of climate change can take place and highlight the moderating role of social ties.

Our findings add to the environmental management literature in three ways: First, we have shown that social ties among stakeholders are complex and multidimensional, and studies that employ SNA frameworks and tools should account for this complexity. We used three social networks that emerged through participation and a control network for outside the project interaction. In this study, all networks had a positive relationship with perceptions of climate change with *Understanding* and *Respect* networks showing the most growth in time and *Influence* showing the most statistically significant association with climate change perceptions. As such, we have shown that perceptions of climate change may not only be influenced via communication ties, but also through relations based on understanding, respect, and influence. Second, our study provides support for stakeholder participation in showing that it leads to network tie formation among participants. In the case of DIPP, descriptive network statistics showed that mutual understanding and respect increased over time. However, future research may further expand on how different aspects of participation (e.g., co-attendance) may lead to tie-formation. As we have shown, understanding, respect, and influence ties can predict learning, and so our study may be seen as providing a positive evaluation of the DIPP process. Third, our study provides a methodology to evaluate social learning in stakeholder participation that directly accounts for the number and strength of social networks; something that is not common in the EM literature that employs SNA.

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4. LEARNING TO UNDERSTAND: DISENTANGLING SOCIAL LEARNING PROCESSES IN STAKEHOLDER PARTICIPATION IN CLIMATE CHANGE ADAPTATION

ABSTRACT

Stakeholder participation is discussed in the literature as positively contributing to climate change adaptation. Although a great deal of interest exists for understanding the role of networks in stakeholder participation little attention is given to applying a network approach in a systematic way as a means of disentangling the social dynamics linking stakeholder participation to learning and collective action. In this paper, we study the co-evolution of a stakeholder network with stakeholders' views of climate change and link these processes to collective action geared towards addressing climate change impacts. I analyzed three waves of data, using a stochastic actor-oriented model (SAOM), on stakeholders' ties, their co-attendance in participatory events, and their views of climate change risks and adaptation measures. Our findings suggest that stakeholders that co-attended participatory events tended to develop ties based on mutual understanding, but those ties did not necessarily translate to changes in stakeholders' perceptions of climate change. We also found that similarity in climate change views was also a driver in the tendency for forming mutual understanding ties. In reflecting on these results in the context of the present study and literature on

environmental governance, we argue that mutual understanding ties among stakeholders are likely to support collective adaptation action more so than individual social learning.

4.1 INTRODUCTION

Stakeholder participation is increasingly seen as valuable and necessary in developing both short and long term adaptation responses to climate change risks (Barrutia and Echebarria, 2019; Galappaththi et al., 2019; Sandström et al., 2014; Sautier et al., 2017). The environmental governance literature highlights the role of stakeholder participation as facilitating social learning and collective action (Cundill and Rodela, 2012; Hassenforder et al., 2016; Sautier et al., 2017; Shackleton et al., 2019; Trimble and Berkes, 2013), and achieving sustainable solutions for a range of environmental problems (de Vente et al., 2016; Lauer et al., 2017). Social networks have been discussed both as an important outcome of the participatory process (e.g., Bodin, 2017; Plummer et al., 2017; Sayles and Baggio, 2017), but also as providing the necessary channels for participants to share knowledge, advice, and hence learn from one another (Lankester, 2013; Matous and Todo, 2015; Rathwell et al., 2015; Schwilch et al., 2012). Although such work supports the general argument that social networks are important for environmental governance (Bodin, 2017; Bodin and Crona, 2008; Bodin and Prell, 2011; Crona et al., 2011; Prell et al., 2009), several questions remain unanswered regarding the underlying social processes that link participation to tie formation, and from tie formation to learning and collective action (Cundill and Rodela, 2012). For example, a number of conceptual and/or qualitative studies on social learning identify various kinds of ties, such as trust, respect, or understanding (Schwilch et al., 2012; Sschusler et al., 2003; Trimble and Berkes, 2013), that emerge over time in participatory contexts, yet quantitative measures of these type of networks have not been widely developed, nor have they been systematically tested in relation to stakeholder participation, social learning, and/or collective action. As such, it remains unclear how these processes are linked together, through social networks, and whether some of these processes prove more relevant/significant than others. Taken together a number of social processes identified within the social learning and participatory literature could benefit from a more structured, longitudinal network study that captures, models, and hence clarifies various tendencies discussed in the literature.

In this study, we use a network approach to build a conceptual framework for evaluating a participatory project situated in Chesapeake Bay, Maryland, USA. This area has already experienced several impacts arising from sea-level rise and is projected to increase to 2 – 6 feet by 2100 (Boesch et al., 2018). The participatory project we consider is the Integrated Coastal Resiliency Assessment (ICRA), a collaborative research project that took place between 2016 – 2018. The ICRA was led by a transdisciplinary group of scientists, who involved local residents and representatives of the state, county, and municipal government organizations, in an iterative collaborative process, over the course of 2.5 years, with the aim of increasing mutual understanding among experts, locals, and government representatives regarding climate change impacts and risks in the area, and to produce collaborative adaptation recommendations, based on this understanding (Paolisso et al., 2019). As such, the main goal and output of this project were to generate a collaborative research report summarizing participants' collective understandings of the vulnerabilities of the Peninsula in the face of climate change (www.dealislandpeninsulapartners.org/collaborative-field-assessments). A secondary, unintended output emerged from the ICRA, which was the securement of State funding for addressing shoreline erosion on the DIP (see details, https://www.dealislandpeninsulapartners.org/). This funding was pursued by the government and local ICRA participants and was developed in response to issues that emerged from ICRA discussions and workshops.

At the outset of the ICRA, longitudinal network analysis was employed to capture the formation of social ties among participants and assess how these social ties co-evolved with participants' perceptions of climate change. Towards that end, three waves of network data focused on two kinds of relations were gathered by members of the ICRA team, both of which were inspired by the collaborative learning (Daniels and Walker, 2001; Feurt, 2008; Johnson et al., 2018; Miller Hesed et al., 2020) and social learning (Meadow et al., 2015; Reed et al., 2010; Rist et al., 2006; Schwilch et al., 2012; Sschusler et al., 2003) literature. These were stakeholders' *co-attendance* in ICRA meetings and events, which was seen as a measure of stakeholder participation, and stakeholders' mutual feelings of *understanding* about their own and others' views of climate change. These network data were gathered via an online survey which also contained questionnaire items measuring stakeholders' perceptions of climate change. These perception measures, moreover, were developed by anthropologists on the team who had been working in the DIP area for a number of years (Paolisso et al., 2019; Van Dolah, 2018), and hence inductively developed questionnaire items that reflected views heard in the field for quite some time prior to launching ICRA.

In studying the co-evolution of social ties and climate change perceptions, we seek to add to the literature on the role of stakeholder networks and social learning in supporting collective action (Adger, 2003; Bodin, 2017; Calliari et al., 2019). In particular, by teasing apart the ways in which participation, mutual understanding, and climate change perceptions are linked together.

4.2 CONCEPTUAL FRAMEWORK

To address the aim of this study, we develop a conceptual framework that links processes of stakeholder participation, with those of mutual understanding, social learning, and collective action. By *stakeholder participation*, we mean the deliberative process in which a diverse set of relevant actors engage in an iterative, ongoing set of discussions and/or activities to develop a deeper understanding of an environmental management issue and potentially, arrive at a more suitable governance solution (Anggraeni et al., 2019; Reed, 2008). Such a participatory process is often conceived with a clear management objective (Sschusler et al., 2003), such as a collaborative research goal (as was the case of the ICRA), or identifying new management mechanisms and policies (Cooper and Wheeler, 2015; Shameem et al., 2015). Social networks are often discussed as playing an important role in stakeholder participation, in that they facilitate knowledge exchange (Lankester, 2013; Trimble and Berkes, 2013), communication (Trimble and Berkes, 2013), collaboration (Bodin et al., 2017), and collective action (Kochskämper et al., 2016). *Social networks* refer to social relations linking a set of stakeholders together, and in the case of the ICRA, we consider the frequency of attendance in ICRA activities as a proxy measure for varying levels of participation among stakeholders., as well as networks based on stakeholders' perceptions of understanding of one another's views. Social networks are also discussed as having an important role in supporting social learning processes among stakeholders (Reed et al., 2010; Sautier et al., 2017). By *social learning,* we mean changes in individuals' views, beliefs, and/or knowledge resulting from the ongoing interactions among individuals involved in a participatory process (Lankester, 2013; Matous and Todo, 2015; Prell et al., 2011; Reed et al., 2010; Sschusler et al., 2003; van der Wal et al., 2014).

Such a definition coincides with SNA notions of 'social influence', where social ties are assumed to predict changes in views, perceptions, and behaviors (Hadden and Jasny, 2017; Leenders, 2002). A similar process is also discussed in innovation diffusion literature (Burt, 1987; Weenig and Midden, 1991), where individuals are seen to 'adopt' the views and/or behaviors of those to whom they are socially tied. In other cases, however, learning on the individual level can mean that participants do not inherently change their views, but rather simply develop a greater awareness and understanding of how other stakeholders think about the environmental issue under question (Walker and Daniels, 2019). From a network perspective, this second version of individual social learning has less to do with social influence processes, i.e.

individuals changing their views in accordance to those with whom they are tied, and more to do with building or strengthening ties of understanding with others from a different background or perspective. In the remainder of the text, when the concept of social learning is used, we mean the individual's change in perceptions or beliefs as a result of being exposed to the perceptions or beliefs of others with whom s/he is socially tied (van der Wal et al., 2014).

Given the multiple definitions and social processes underpinning participation, social learning, and collective action, the goal of this study is to disentangle the role of participation in social learning, both at the group and individual levels. These processes of participation, mutual understanding, and social learning are further discussed below.

4.2.1 PROCESS A: STAKEHOLDER PARTICIPATION LEADS TO MUTUAL UNDERSTANDING TIES

The literature on collaborative, environmental decision making supports the idea that participatory processes provide opportunities for diverse, heterogeneous stakeholders to share their opinions and beliefs about environmental management issues (Daniels and Walker, 2001; Ernoul and Wardell-Johnson, 2013; Lumosi et al., 2019; Paolisso et al., 2019; Rist et al., 2006), which in turn facilitates mutual understanding among participants (Hegger and Dieperink, 2014; Mostert et al., 2007; Rist et al., 2006). Through frequent, iterative discussions, stakeholders learn about one another's views, knowledge, and belief systems, and in doing so, gain a wider understanding of how other stakeholders think about and approach the environmental problem. The goal is *less* about stakeholders arriving at a similar set of opinions regarding environmental governance, and *more* about enabling environmental solutions to collectively arise, in spite (or because) of participants' diverse views and beliefs. If done successfully, stakeholder participation should lead to increased feelings of being both heard and understood among participations (Lumosi et al., 2019; Mostert et al., 2007; Reed et al., 2010; Rist et al., 2006; Schwilch et al., 2012), where stakeholders may (or may not) hold similar views regarding the environmental problem in question, and where stakeholders nonetheless develop a collective response to this problem (Ostrom, 2010; Rist et al., 2006; Tompkins and Adger, 2004; Walker and Daniels, 2019). In this line of reasoning, participation can be seen as leading to mutual understanding among participants and collective responses (Daniels and Walker, 2001; Johnson et al., 2018; Miller Hesed et al., 2020; Paolisso et al., 2019; Walker and Daniels, 2019). (Lauer et al., 2017). Such a process is captured below (Figure 7; **Process A**). We phrase this process as the following hypothesis:

H1: *Stakeholder participation leads to mutual understanding between co-attending stakeholders.*

4.2.2 PROCESS B: STAKEHOLDER PARTICIPATION LEADS TO SOCIAL LEARNING VIA SOCIAL INFLUENCE

The second process we identify is depicted as **process B** (Figure 7). Here, stakeholder participation fosters social learning by generating multiple opportunities through which participants can share knowledge and learn from one another. The process of participation offers stakeholders frequent exposure to other participants, where interactions provide channels for explicit and implicit information flows regarding environmental problems and management issues (Sandström et al., 2014). Such exposure to the perceptions and beliefs of others and may lead individual participants to modify their views and/or behaviors regarding an environmental issue (e.g., Crona et al., 2011; Hassenforder et al., 2016; Muter et al., 2013; Sautier et al., 2017; Sschusler et al., 2003). Lumosi et al. (2019) refer to this process as *learning spaces*, where social learning arises within processes of social interaction, and where changes in individual perceptions is assumed to be the result of just being part of participatory spaces; namely, co-attending the same events (Rathwell et al., 2015; Shackleton et al., 2019; van der Wal et al., 2014). In this process, the action of attending the same participatory events with other stakeholders, some of whom may hold different views on an environmental issue and becoming aware of those views in a participatory setting is expected to result in individuals adopting new, influenced, views (Prell et al., 2010). This process is summarized in the following hypothesis:

H2: *Stakeholder participation leads to social learning among co-attending stakeholders.*

4.2.3 PROCESS C: MUTUAL UNDERSTANDING AND SOCIAL LEARNING

Other literature seems to suggest that there might be an intermediary process by which participation is linked to individual social learning (e.g., Van Der Wal et al., 2013). Here, as shown in Figure 7 as **Process C**, participation creates opportunities for stakeholders to first develop mutual understandings of one another's beliefs, values, and knowledge, and this mutual understanding provides the basis upon which stakeholders begin to influence one another's views, beliefs, and knowledge, thus leading to an increased, shared view of the environmental problem and potential solution(s) (Crona et al., 2011; Muter et al., 2013; Rist et al., 2006; Schwilch et al., 2012). Thus, it is via the intermediary process of mutual understanding that participation may lead to changes in perceptions regarding climate change.

The role of social networks as a moderating mechanism within participatory mechanisms have been recorded before in the context of stakeholder learning (Crona et al., 2011; Cundill and Rodela, 2012; Lankester, 2013; Schwilch et al., 2012). This form of social learning is closely related to the theories of social influence and social contagion in social network analysis literature (Burt, 1987; Doreian, 1989; Leenders, 2002), which conceptualize the change in an actor's attributes as a result of the actor's embeddedness in a social network. As the number of ties increases for an individual, so is the likelihood of that person changing his/her views based on the views of networked partners, thus enabling the process of social influence (Burt, 1987; Doreian et al., 1989; Leenders, 2002). Studies across a range of empirical contexts have given support for social influence (e.g., Christakis and Fowler, 2013; Friedkin, 2001; Marsden and Friedkin, 1993). This process is phrased in the following hypothesis:

H3: *Stakeholder participation facilitates mutual understanding ties among co-attending stakeholders, which in turn leads to social learning.*

4.2.4 PROCESS D: HOMOPHILY-DRIVEN TIE FORMATION

Whereas the first three hypotheses considered the routes through which participation can be linked to mutual understanding and/or social learning, our final process considers the role climate change perceptions may play. As networks may 'work on themselves' in a dynamic fashion, teasing apart whether ties drive changes in perceptions, or the reverse, is an important consideration for longitudinal studies. Thus, a final process we consider is based on the theory of homophily, or social selection(McPherson et al., 2001; Newman and Dale, 2005). Here, as shown in **Process D** (Figure 7), the similarity in climate change views among stakeholders acts as a predictor for the tendency of forming mutual understanding ties. Actors prefer to establish social relations with others who are similar to themselves, regardless of the engagement setting (Skvoretz, 1990, 1985). In the context of climate change adaptation, we would expect that actors that share similar perceptions about climate change will feel understood by each other. In the case of co-attending ties, we would expect actors to co-attend the same events if they share similar views and perceptions of climate change. In general, this process captures (and controls for) the dynamic relation between actors' perceptions and tie-formation behavior (Steglich et al., 2010). This process is summarized in the following hypothesis:

H4: *The tendency for mutual understanding and co-attendance is more likely to occur among actors sharing similar views of climate change*

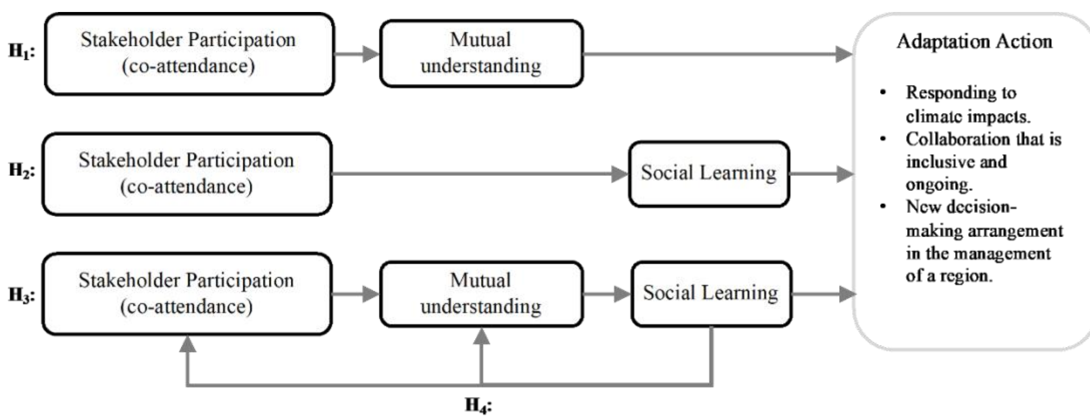


Figure 7: Conceptual map of research approach, different pathways in which stakeholder participation may lead to collective action.

Taken together, we test these four processes outlined in the literature through longitudinal network analysis on a stakeholder network in the Deal Island Peninsula, Maryland, USA. The methods and analytical approaches are detailed below.

4.3 MATERIALS AND METHODS

Network data and individual attribute data were collected at three time periods between 2016 – 2018. The first wave of data collection occurred after only two meetings occurred. The second wave of data were collected after a total of eleven participatory events occurred, and the final wave of data were gathered after a total of 14 participatory events occurred. Participatory activities included workshops and field research evaluations geared toward issues of flooding, coastal erosion, conservation and restoration of marshes and possible actions that may address those issues (see Johnson et al., 2017 for a detailed account of the collaborative activities).

A sample (n = 60) of stakeholders were considered as active participants in this study and included resource managers from state and local governments (n=21), a multidisciplinary group of scientists based in the region (n=23), and local community members (n=16). To measure the network of mutual understanding among these stakeholders, we used a roster including all ICRA participants' names, and asked respondents to rate each ICRA participant via the following statement: "I feel that this person understands my views regarding the ICRA area." Answers for this item ranged from 1 ('a little') to 2 ("somewhat") to a maximum of 3 ("a lot"). These data thus provided a valued, actor by actor matrix. To measure stakeholder participation, we converted the attendance sheets for all ICRA meetings into three, valued, actor-by-actor matrices, in which the values in each cell of the three matrices represented the number of ICRA events each pair of actors co-attended. The first co-attendance matrix reflected stakeholders' ICRA participation prior to the first wave of data gathering, the second matrix held co-attendance data for stakeholders between the first and second wave of data gathering, and the final co-attendance matrix represented the total number of co-attended meetings of participants between the second and third wave of data gathering.

Questions on climate change perceptions included seven 4-point Likert statements (Table 6). These questions were inductively derived by anthropologists on the team who had been researching the DIP area prior to the project's launch. As such, these statements reflect views and perceptions of climate change that anthropologists had heard in their qualitative field work. Participants were asked to rate the statements depending on how much they agreed or disagreed with each statement. Individual statements were intended to gauge the perceptions of the respondent on climate change awareness, risks, and actions. The responses had high internal reliability (Cronbach α = 0.96) and were combined into a single averaged score. This score can be interpreted as a person's overall level of awareness of the causes and impacts of climate change in their community. Data collection occurred at the beginning, middle, and end of the project's duration.

Table 6: Climate change perceptions statements (Cronbach $\alpha = 0.96$)

1. The climate is changing in different ways from before due to the impacts of human activities.
2. Climate change is affecting the communities of the Deal Island Peninsula already.
3. Climate change is affecting the environment of the Deal Island Peninsula already.
4. The Deal Island Peninsula area will experience more storms and floods in the future due to climate change.
5. The resilience of Deal Island Peninsula communities will be reduced in the future due to climate change.
6. Climate change is a significant threat to the social and ecological system of the Deal Island Peninsula.
7. Building relationships with people and organizations that have an interest in the Deal Island Peninsula and can help communities cope with climate change.

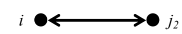
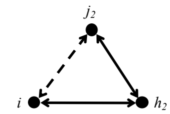
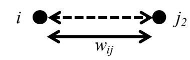
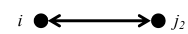
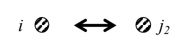
In order to disentangle the different mechanisms of stakeholder participation that are proposed here (Figure 7), we applied the stochastic actor-based network model (Snijders et al., 2010; Steglich et al., 2010), which is implemented through the R package RSiena (Snijders, 2017). This methodology models changes in longitudinal network data in consecutive steps. On each step, the tendency for an actor to change his or her surrounding network structure is considered, based on the specific dynamics the researcher is interested in. Siena can simulate the co-evolution of the network with actors' perceptions by simultaneously estimating network structure as a function of behavioral information (network dynamics) and vice versa (behavioral dynamics) at every time step. We introduced the *mutual understanding* and *co-attendance* networks as dependent network variables in the RSiena package, and *climate change perceptions* as a dependent actor attribute variable in the behavioral dynamics part of the model.

In order to test our 4 hypotheses, we specified 6 network and behavioral effects in our modeling framework. These are as follows; for testing the first hypothesized process (Figure 7, **Process A**), we used the *crprod* effect, which captures the tendency of actors who co-attend, to then form mutual understanding ties. For **Process B**, we used a *total similarity (totSim)* effect, which captures the tendency of actors to change their climate change perceptions as a function of the perceptions of their co-attending partners. For the third hypothesized process (**Process C**), we used the *crprod* effect, as well as the *total similarity (totSim)* effect. These two effects capture, on the one hand, the tendency of actors to form mutual understanding ties with those whom they co-attend ICRA meetings, as well as the tendency of actors to change their perceptions as a function of the perceptions of those with whom they share a mutual understanding tie. Finally, the last process (**Process D**) includes a *covariate-similarity (simX)* effect, which captures the tendency for ego to make ties with those having similar climate change perceptions. In addition, we include *same-covariate (sameX)* effect to capture the tendency of actors to form network ties with others in the same stakeholder category.

Additionally, SAOMs include default controls of *rate effects* for both the network and behavioral models. For the network (tie-formation) model, the rate parameter indicates the degree to which actors have the opportunities to change their ties. For the behavioral (perception-change) model, the rate parameter controls the opportunity for actors to change their perception values from one wave to the next. Moreover, a linear and quadratic shape effects are included as default controls in the behavioral model, and together capture the overall tendency towards high or low *perception* values and the effect of the actor's *perception* value on itself, respectively (Snijders et al., 2010). A full list of these network and behavioral effects are displayed, with accompanying formulas, in Table 7.

In using the RSiena model, the following two steps were taken: First, the valued matrices for mutual understanding and co-attendance were dichotomized. In the case of mutual understanding network, tie strength values of 2 and 3 were transformed to 1 and ties values of 1 were transformed to 0. This transformation approach was adopted for being conservative in that it considered only stronger ties in the analysis. In the case of the co-attendance matrix, we took a liberal approach transforming every non-zero value into 1. This approach assigned a coattending tie between two individuals if at least they had co-attended at least one meeting. This approach was adopted due to the varying range of participatory meetings that occurred between survey data collection. Second, as these data were symmetrized matrices, we specified in the Rsiena algorithm a model type 2 (forcing model), which imposes that actors can take initiative and unilaterally create or dissolve a tie (Ripley et al., 2019, p. 51). Finally, As the amount of attendance in ICRA meetings varied from one period to the next, we made the choice to run two separate models, and in this way controlled for the time heterogeneity inherent in the data. When working with two or more periods, i.e., three or more waves, within RSiena, there is a concern regarding whether parameters are constant across the periods. If there is a great amount of change in the network between two consecutive observations, this can result in biased inferences (Lospinoso et al., 2011; Ripley et al., 2019, p. 97). One means of handling this is to model the periods separately, so that the modeled amount of change in one period does not impact that of the other.

Table 7: SAOM effects included in the modeling framework

Effect name	Underlying social network tendency	Mathematical formula	Graphical representation
Endogenous network effects			
Degree	The basic tendency to create and maintain ties	$\sum_j x_{ij}$	
Transitive Triads	Establishing ties with actors who have ties with ego's alters; this tendency leads to click formation	$\sum_{j,h} x_{ij}x_{ih}x_{hj}$	
Network formation effects			
Network W on X	The tendency for actors that share tie in network W to establish a tie in network X	$\sum_j x_{ij}w_{ij}$	
Covariate similarity	Establishing a tie with others that have similar covariate values	$\sum_j x_{ij}\left(sim^v_{ij} - \widehat{sim^v}\right)$	
Covariate same	Establishing a tie with others that have the same covariate values	$\sum_j x_{ij} I\{v_i = v_j\}$	
Covariate-ego	The tendency of an actor with a certain covariate value to form ties	$v_i x_i +$	
Perception change effects			
Overall linear, quadratic growth	Tendency of individuals to change perceptions that is not related to observed networks	$z_i; z_i^2$	
Total similarity in perceptions	Peer influence, i.e., adopting the perceptions of alters, where the total influence of alters is proportional to the number of alters	$\sum_j x_{ij}\left(sim^z_{ij} - \widehat{sim^z}\right)$	

4.4 RESULTS

4.4.1 DESCRIPTIVE RESULTS

Descriptive characteristics of the co-attendance and understanding networks at the three time points are found in Table 8. The amount of changes between the 3 measurement moments was expressed by a Jaccard coefficient of 0.250 and 0.273 between period 1 (wave 1 and 2) and period 2 (wave 2 and 3), respectively, for the mutual understanding network. This coefficient expresses the amount of change between two consecutive waves within a range from 0 to 1 (with 1 representing no change). The Jaccard coefficient for co-attendance network was 0.287 and 0.261 for periods 1 and 2, respectively. These coefficient values lie within the normal, suggested range for using SAOMs (see p.20, Ripley et al., 2019). Network characteristics for every data period is found in Table 8, including overall density and average degree for each network.

Table 8: Descriptive statistics of network characteristics

	Wave 1			Wave 2			Wave 3		
	Ties	Density	Avg. degree	Ties	Density	Avg. degree	Ties	Density	Avg. degree
Understanding	99	0.056	3.300	156	0.088	5.200	161	0.091	5.373
Co-attendance	363	0.205	12.10	256	0.145	8.53	174	0.098	5.80

Based on descriptive statistics, it is noticeable that the mutual understanding network is growing over time; increasing in number of ties, density, and average degree. On the other hand, co-attendance network experiences a reduction over time. Stakeholder attributes, namely the individual scores of climate change perceptions (range 1 – 5) for each wave are described in Table 9.

Table 9: Stakeholder attribute

	Wave 1			Wave 2			Wave 3		
	Mean	SD	Missing	Mean	SD	Missing	Mean	SD	Missing
Climate change perception	4.415	(1.02)	19	4.192	(1.29)	8	4.167	(1.34)	18

4.4.2 RESULTS FROM LONGITUDINAL ANALYSIS

Starting with Model 1a and 1b, the default *rate parameter* indicates slightly more tie changes occurring in the second period than the first for understanding network. The negative, significant coefficient for the *degree* effect indicates that stakeholders avoid forming too many understanding ties overtime. A third default *transitive triads* effect indicates the positive and significant tendency for actors to form transitive triads. With regards to default controls for the behavioral change part of the models, the *rate* parameter in Climate Change Perceptions shows a tendency of individuals to change their perceptions at similar degrees in both periods. In addition, both linear and quadratic shape coefficients are not significant. As these findings for the default controls remain largely the same across all models (Models 2a – 3b), we will not comment on them further.

We now begin discussing the results for our hypothesized effects. The first set of models (Table 10) account for network dynamics for period 1 (wave 1 and 2) and the second set of models (Table 11) accounts for changes in period 2 (wave 2 and 3). The same set of network effects were used for both modeling periods to ensure that the same tendencies were modeled consistently across both periods. In addition, both sets of models were generated in a step-wise fashion in order to first highlight hypothesized tendencies, before building more complex models with competing network effects.

The results of hypothesis 1, which predicts the tendency of network partners to form mutual understanding ties given that they co-attend ICRA meetings, are found in models 2a and 2b, as well as models 3a and 3b. Here, we see a significant, positive result across all four models, even when additional, competing network effects are added (Models 3a and 3b). Thus, there is strong support for hypothesis 1.

For testing hypothesis 2, we included the total similarity effect, i.e., the tendency for ego to change perceptions of climate change based on the perceptions of alters in his/her co-attendance network, in the Perception Change component of Models 1a and b. We note that for both models (Model 1a and 1b), there is no significant effect. Thus, hypothesis 2 is not supported.

Results for hypothesis 3 are shown in models 2a and 2b. Hypothesis 3 predicts the role of mutual understanding ties as an intervening process between participation and social learning among stakeholders. In both periods, we see a positive and significant tendency for coattending partners to form mutual understanding ties (same as hypothesis 1) but mutual understanding ties are not significant at predicting changes in perceptions. Thus, our results do not support hypothesis 3.

Table 10: Period 1

H#	Network changes	Model 1a par.	Model 1a (s.e.)	Model 2a par.	Model 2a (s.e.)	Model 3a par.	Model 3a (s.e.)
	Network: *Mutual-Understanding*						
	Rate	6.886***	(1.127)	6.650***	(1.291)	6.696***	(1.113)
	Degree (density)	–1.662***	(0.116)	–1.783***	(0.144)	–2.065***	(0.179)
	Transitivity (triads)	0.422***	(0.053)	0.416***	(0.053)	0.437***	(0.055)
H4	Climate perceptions (similarity)					0.969*	(0.469)
	Climate perceptions (ego)					–0.215	(0.173)
	Stakeholder type (same)					0.470**	(0.178)
H1,3	*Co-attendance* effect			0.450*	(0.221)	0.492*	(0.243)
	Network: *Co-attendance*						
	Rate	30.661***	(8.965)	30.375***	(8.140)	31.811***	(15.504)
	Degree (density)	–1.949***	(0.144)	–1.952***	(0.160)	–1.963***	(0.192)
	Transitivity (triads)	0.166***	(0.010)	0.166***	(0.011)	0.165***	(0.013)
H4	Climate perceptions (similarity)					0.004	(0.368)
	Climate perceptions (ego)					–0.087	(0.133)
	Stakeholder type (same)					0.113	(0.204)
	Perception changes						
	Climate perceptions						
	Rate	0.977**	(0.433)	1.015**	(0.396)	1.020**	(0.428)
	Linear shape	1.011†	(0.599)	1.165*	(0.572)	1.161†	(0.593)
	Quadratic shape	0.884	(0.973)	0.686	(0.523)	0.688	(0.470)
H3	Total similarity – *Mutual understanding*			–0.046	(0.612)	–0.038	(0.762)
H2	Total similarity – *Co-attendance*	0.175	(0.647)				

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Finally, Models 3a and 3b address hypothesis 4 by including homophily effects that captured the extent to which mutual understanding and co-attendance ties were driven by homophily. Here, our results show evidence of homophily-driven tie-formation tendencies for both understanding and co-attendance networks. The *ego covariate activity* effects show that actors with high values of climate change perceptions tend to decrease their tie-formation behavior, although this effect is only significant during period 2 for mutual understanding and is not significant in either period for co-attendance ties. The *similarity* effect, which captures the tendency for actors to establish ties with others holding similar perception values, is positive and significant for mutual understanding ties during both periods (Models 3a and 3b). Co-attendance similarity is not significant at either period. These results show a partial support for hypothesis 4, suggesting that there is a tendency among ICRA stakeholders to form mutual understanding ties with those holding similar views and a tendency of actors holding higher values on climate change perceptions to form less ties overall. On the other hand, climate participants that coattend the same events do not do so because of similar views.

With regards to model-fit, we refer readers to the goodness of fit (GOF) tests for Models 3a and 3b to section *III.1 Goodness of Fit Tests for SAOM Models*, which demonstrate that we have adequately captured network patterns in our empirical networks via our model specifications.

Table 11: Period 2

H#	Network Changes	Model 1b par.	Model 1b (s.e.)	Model 2b par.	Model 2b (s.e.)	Model 3b par.	Model 3b (s.e.)
	Network: *Mutual-Understanding*						
	Rate	9.150***	(1.426)	8.474***	(1.351)	9.125***	(1.618)
	Degree (density)	–1.815***	(0.117)	–1.940***	(0.129)	–2.266***	(0.182)
	Transitivity (triads)	0.412***	(0.042)	0.370***	(0.046)	0.389***	(0.049)
H4	Climate perceptions (similarity)					1.464**	(0.523)
	Climate perceptions (ego)					–0.479**	(0.165)
	Stakeholder type (same)					0.441**	(0.152)
H1,3	*Co-attendance* effect			0.845 ***	(0.252)	0.928***	(0.264)
	Network: *Co-attendance*						
	Rate	18.478 ***	(5.556)	18.525 ***	(4.240)	16.748***	(4.187)
	Degree (density)	–2.438 ***	(0.244)	–2.433 ***	(0.245)	–2.980***	(0.487)
	Transitivity (triads)	0.266 ***	(0.026)	0.265 ***	(0.025)	0.307***	(0.039)
H4	Climate perceptions (similarity)					0.130	(0.697)
	Climate perceptions (ego)					0.422	(0.428)
	Stakeholder type (same)					0.353	(0.268)
	Perception changes						
	Rate	0.816*	(0.420)	0.793*	(0.367)	0.767*	(0.378)
	Linear shape	6.123	(31.152)	1.903*	(0.967)	1.978†	(1.024)
	Quadratic shape	–2.994	(20.852)	0.158	(0.369)	0.183	(0.387)
H3	Total similarity – *Mutual understanding*			–0.761	(0.814)	–0.844	(0.946)
H2	Total similarity – *Co-attendance*	–6.819	(42.465)				

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

4.5 SUMMARY AND DISCUSSION

We used a network approach to take a deeper look at the social processes discussed in relation to participation, social learning, and collective action. In particular, our findings indicate the following:

In terms of what participation accomplishes, we demonstrated that co-attending meetings (i.e. participation) lead to significant, positive feelings of mutual understanding among stakeholders, even when controlling for a number of other processes. In the context of ICRA, such processes can be interpreted as participation being a positive driver for creating social conditions (such as feelings of understanding) upon which a collective action—in this case, a collaborative research report—can take place.

Further, we also show that the above findings hold, even when we consider the real possibility, often discussed in the network literature, of actors selecting others with whom they share similar views (i.e. the homophily effect). Although evidence was found for the tendency of actors to feel understood by those who share similar views as themselves, this tendency did not overshadow the impact that co-attendance had on stakeholders forming ties of understanding over time. As such, we were able to disentangle the extent to which mutual understanding was a result of co-attendance (hypothesis 1 & 3) versus homophilous views of climate change (hypothesis 4). In our case, both tendencies were present.

Finally, our findings suggest no support for social learning, i.e. actors becoming more similar overtime in their climate change perceptions. Being connected to others via co-attendance or mutual understanding did *not* lead to actors becoming more similar in their climate change views. Thus, in the context of ICRA, failing to influence others to acquire similar views as one's own seems to matter very little when contributing to the collective effort of researching DIP vulnerabilities.

In relation to the literature, we thus make the following contributions: We systematically tested two often discussed outcomes of participatory processes in the context of environmental processes: social learning (as a form of social influence) and mutual understanding. A network approach enabled us to disentangle the extent to which participation impacted changes in climate change perceptions and/or feelings of understanding. As both processes are linked to collective action, our findings give support to the argument that collective action is possible, even when stakeholders steadfastly fail to influence one another's views.

These findings also add to the foundation of research that examines the epistemology of social learning in sustainability science and climate change adaptation. The definition of social learning as "a change in understanding," (García-Nieto et al., 2019; Plummer et al., 2017a; Reed et al., 2010) has also been operationalized in relation to the network theory of social influence (Bentley Brymer et al., 2018; Crona et al., 2011; Matous and Todo, 2015), and although our results, on the one hand, fail to provide support for this tendency for stakeholders to influence one another's views, we nonetheless provide support to notions of social learning at the group level, where there are a joint problem understanding and decision-making which leads to improved management of the environmental system and collective action (Lumosi et al., 2019; Mostert et al., 2007; Pahl-Wostl, 2009; Paolisso et al., 2019). This form of learning has been well articulated in the collaborative learning literature (Johnson et al., 2018; Miller Hesed et al., 2020; Walker and Daniels, 2019). The research presented in this paper explores competing definitions of social learning and sets the bases for future studies to increase scholars' understanding of the rich, social dynamics that emerge through stakeholder participation in natural resource management, sustainability science, and in our case climate change adaptation.

Future research may consider additional networks in the analysis including how social networks of trust and respect affect the formation of understanding ties and/or affect co-attendance. These additional networks may also be tested for their effects on stakeholders' views on climate change. Further, the understanding of the social dynamics that lead to social learning may benefit from a mix-methods approach, i.e. combining SNA results with those from participant-observation and/or qualitative interviews, in order acquire a deeper understanding of how and why stakeholders acquire their particular climate change views and/or form particular ties with others.

Limitations of this study include the following: First, this study only considers one social relation (i.e. mutual understanding) that might arise from participation. In the literature, mutual understanding is only one of many relations that get noted (e.g. mutual respect, trust, and collaboration) as potential outcomes of participation. As such, future research could test additional social relations mentioned in the literature. Second, and perhaps most importantly, the time-constraints imposed by the research design (in our case, the study design was limited to 2.5 years) may not have been long enough to enable our research team to capture changes in perceptions overtime. In particular, with a longer time window, one may indeed observe stakeholders becoming more similar overtime in their views. In such a scenario, the first intermediary step is the 'hard work' of creating ties based on feelings of mutual understanding. Thus, whether stakeholders, over a longer period, change their views to resemble those of their co-participants remains an open question.

4.6 CONCLUSION

Stakeholder participation plays a much-needed role in responding to climate change by bringing together individuals with diverse forms of knowledge. This paper explores the social dynamics that lead to or support the emergence of social learning. We tested multiple literature-based hypotheses regarding the role of participation and ties of mutual understanding in explaining social learning, as a change in individual perceptions, and its relation to collective action. Yet as already noted above, the limitations on time and resources in the present study leave a number of number of open questions regarding the precise role networks play in shaping participatory outcomes in relation to climate change adaptation. Our study presents a blue print for future research on longitudinal network studies focusing on participation processes in relation to climate change.

ACKNOWLEDGEMENTS

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5. DISCUSSION AND CONCLUSION

In this dissertation, I contributed to the scientific literature on stakeholder participation in general, specifically exploring the relation between perceptions of climate change and social networks. This chapter summarizes the contributions of the research presented in this dissertation, explore policy and practical implications of findings, describe the limitations, and provide future research directions. A set of final remarks concludes this dissertation.

5.1 SYNTHESIS OF CONTRIBUTIONS

In Chapter 2, I employed a systematic review approach to climate change literature (scientific and non-academic) to assess the knowledge, data, and stakeholder landscape of the Chesapeake Bay. The review provided a geographical context to the dissertation and answered two main questions: (i) how are indicators of climate impacts measured and reported by different types of authors, document types, and geographic focus? And, (ii) what are the current approaches for measuring the most pressing climate impacts in Maryland and the Chesapeake Bay? I found that data and indicators of climate change impacts are predominantly measured at the state or Chesapeake Bay level, which leaves county and municipal managers lacking the knowledge to implement adaptation strategies. Furthermore, authorities and the general public are concerned about the efficacy of adaptation measures (e.g., agricultural BMPs, green infrastructure, and socio-economic policies). As such, I identified a growing trend in participatory research being employed as an approach to engage a wider range of stakeholders and solicit information that may lead to better adaptive and collaborative management. These approaches are conducive to the co-creation of knowledge and may achieve the interactions needed between scientists, government, and civil society that may enhance the adaptive capacity to climate change. Overall, this review expands the understanding of the information network in the Chesapeake Bay and explores the institutional landscape of stakeholders involved in the production and consumption of environmental and social change data.

In Chapter 3, I found a positive and significant relationship between the social networks of stakeholders and their perceptions of climate change. In other words, stakeholders' ties of mutual understanding, respect, and influence with others, multiplied by the weighted sum of networked-partners' perceptions, can predict the perceptions of the individual stakeholders. Results suggest that if the summed climate change perceptions of the networked partners of actor A increase, then there is a significant likelihood actor A's perceptions of climate change will increase. This relationship exists for social networks of mutual understanding, respect, influence, and outside-project interaction. These results do not take into consideration the dynamics of tie formation overtime, and/or how perceptions and ties can co-evolve, and hence, impact one another. This study does provide evidence of the role of social networks in stakeholder perceptions. In accordance with the environmental management literature, Chapter 3 concludes that certain social processes are important in relation to the process of participation, especially those that are associated with learning and stronger social networks.

In Chapter 4, I built on Chapter 3 by considering not just the impact of networks on perceptions, but also the impact of perceptions on network ties, as well as the endogeneity of network formation. As such, identifying the drivers behind the formation of mutual understanding ties were as important in the inquiry as understanding the drivers behind climate change perceptions. Although evidence was found for the tendency of actors to feel understood by those who share similar views as themselves, this tendency did not overshadow the impact that co-attendance had on stakeholders forming ties of understanding over time. Further, being connected to others via co-attendance or mutual understanding did not lead to actors becoming more similar in their climate change views (i.e., social learning). We interpreted these findings as such: in the context of ICRA, failing to influence others to acquire similar views as one's own seems to matter very little when contributing to the collective effort of addressing local vulnerabilities. Yet as we note here, in this chapter, we can see that one future study should focus on testing (via simulation techniques) the role network size might play in ascertaining the predictive power of ties on climate change perceptions. Chapter 4 thus contributes to the literature in the following way: the network approach enabled the disentangling of the extent to which participation impacted changes in climate change perceptions and/or feelings of understanding. As both processes are linked to collective action, these findings give support to the argument that collective action is possible, even when stakeholders fail to influence one another's views.

In summary, the methods and results presented in this dissertation answer to the main goal of the dissertation by providing an in-depth understanding of the ecological, social, and economic impacts of climate change in the Chesapeake Bay, Maryland, and the landscape of stakeholders involved in the region; providing an evaluative framework of stakeholder participation that highlight the role of social networks in supporting learning processes; and testing the co-evolution of networks and perceptions in stakeholder participation to support collective action. In sum, this dissertation provides an in-depth study of participatory science in a coastal region vulnerable to the impacts of sea-level rise.

5.2 POLICY AND PRACTICAL IMPLICATIONS

This work is intended to move forward the understanding and development of adaptation policies and contribute to the overall development of better measures for stakeholder participation that may aid adaptation processes all around the world. The collection of studies that make up this dissertation are in synchrony with goal no. 17 of the United Nations Sustainable Development Goals, which seeks to "encourage and promote effective public, public-private and civil society partnerships, building on the experience and resourcing strategies of partnerships." Adaptation practitioners may use this information and analysis to improve their implementation of participatory processes, giving greater importance to aspects of mutual understanding and respect. Moreover, it is important to acknowledge that different views among stakeholders may not change much or at all. This is not to be interpreted as an unsuccessful outcome of participation, not if other social networks had been developed and strengthen. We have shown that perceptions are not the only factor when it comes to collaborating. Policy-makers and funding agencies may consider requiring projects that employ participatory tools to collect network and perception data, similar to the ones used in this dissertation, as a way to monitoring performance of stakeholder participation over time.

5.3 LIMITATIONS

The reliability of the conclusions presented in this dissertation are constrained by the quality of the data, which can be said for many, if not all, empirical studies. The data used in this dissertation was collected from the participatory project Integrated Coastal Resiliency Assessment (ICRA), which collected perception and social network data from ICRA stakeholders between 2016 – 2018 (the research context was detailed in section 3.2.1, Chapter 3).

One part of the survey captured the perceptions that participants held about climate change. Perceptions of climate change, in my analysis, was a composite variable consisting of the average of 7 Likert-scale items, each of which captured different aspects of climate change beliefs and perceptions. As seen in Table 1 in Chapters 3 and 4, these items did not capture the objective knowledge participants had of climate change science. Rather, they captured their views and perceptions of the risk climate change posed to their communities. It is worth discussing the appropriateness of measuring perceptions of climate change as opposed to measuring objective knowledge of climate change science. The ICRA data was gathered by a team of anthropologists, whose focus was to investigate the underlying cultural influences in participants' beliefs of climate change. Perceptions, beliefs, and views are similar in the way they refer to an individual's values and not knowledge. Thus, the data we gathered reflected concepts and beliefs these anthropologists had heard, witnessed, or observed out in the field, prior to the start of the study. The relation between these two is complex and beyond the scope of this study. Nonetheless, there is a wealth of literature on the study of perceptions (e.g., Akerlof et al., 2016; Bennett, 2016; Gore et al., 2016; Parkinson, 2009; Tam and McDaniels, 2013; Williams et al., 2017), and further research may attempt to try and tease apart *knowledge on climate change* gained from a participatory project, as opposed to the influence a participatory project may have on changing *climate change beliefs*.

The perception data has its limitations. First, the scale of the perception variable ranged from 1 – 4. This presented a constraint given that most ICRA stakeholders scored between 3 and 4; this was because some stakeholders had already been collaborating before the ICRA project and presumably had experienced a degree of perception changes prior to the data collection. It is possible to question whether collecting data at a prior time, when they had not interacted, would have yielded a different distribution of the perception values, which in turn would have influenced the statistical results. This is one of the limitations of this study.

The other part of the survey collected network data, which in Chapter 3 was of size 53, 52, and 42 for waves 1, 2, and 3, respectively. In Chapter 4, the same network data were transformed into 3 square matrices of 60 by 60, for each of the 3 data periods. They are both the same dataset, but the transformation of the data depended on the methodology applied to each study, which in turn depended on the purpose of each study. In Chapter 4, the modeling approach (i.e., the SIENA model) has potential limitations based on the network size of 60 participants over 3 waves of data. Given the aim of Chapter 4 was to simultaneously model the changes in network structure and actors' perceptions, the SIENA model was specified to include effects for both aspects (section 4.3, Chapter 4). But the estimation of the network changes is not equivalent to the estimation of changes in actor perceptions, given that the number of ties is not linear with the number of actors in the network. As Stadtfeld et al. (2018) describe it, for every actor *N* in a network, there are many possible ties, and adding one more actor will exponentially increase the number of possible ties. On the other hand, actor attributes (i.e., perceptions of climate change) are 1-to-1 for every actor, and the estimation space for changes in actors' perceptions is much smaller than changes in network ties.

Stadtfeld et al. (2018) compared the predictive power of simulated network analyses using SIENA on different network data sizes (n = 30, 60, 120) and varying data waves (2, 3, and 5 data waves). They showed that, when simultaneously estimating network changes and behavior changes, a network size of 120 participants and 5 waves of data will provide a reliably high level of predictive power for both processes (above 97.5%). For networks with sizes of 60 participants and 3 waves (like the ICRA data, Chapter 4), then SIENA will estimate with high statistical power the network changes (99.5%) but will have a low estimation power for the perception changes (34.5%). Networks with 30 participants and 2 waves of data provide low power estimations for both network (34.5%) and behavioral (10%) changes. In the context of the present study, one might conclude that low-power of the model, resulting from the small size of the network (n=60) maybe the reason for not attaining significant results for changes in climate change perceptions. Even so, it cannot be said conclusively that the non-significant perception change results from ICRA networks are the result of low statistical power. As discussed in Chapter 4, there is theoretical support from the literature on collaborative learning that suggests that participation is more likely to lead to mutual understanding, and not changes in beliefs or values. Future research may make use of simulation strategies to ascertain the likelihood that larger network sizes may lead to changes in perceptions and/or network patterns (Prell and Lo, 2016; Stadtfeld et al., 2018).

5.4 FUTURE DIRECTIONS

This dissertation is a blueprint to the study of stakeholder networks in climate change adaptation, with respect to their relationship with perceptions, social learning, and collective action. Of course, a larger data set is always better and may provide higher statistical power in the modeling. Beyond data limitations, future research may consider collecting network data on trust, given the theoretical importance of trust in collaboration networks (Bodin et al., 2020; Kettle and Dow, 2016; Metcalf et al., 2015). Moreover, it is also possible that not all types of perceptions are linked to networks in the same way (Muter et al., 2013). As such, testing similar social networks with other forms of perceptions including control perceptions will further expand the understanding of the social processes guiding stakeholder participation and perception studies.

5.5 FINAL REMARKS

To conclude, there is a long road ahead in the study of stakeholder participation and its many contributions to climate change adaptation. It is no longer enough to acknowledge that participation is important in addressing the existential threat of climate change. Collectively, we need to accelerate the study of participation in the direction of standardizing principle of participation that can be measurable, monitored, and comparable across geographic regions and scales and at different stages of the participation process. This dissertation is but one step in that direction.

I. SUPPLEMENTARY MATERIAL FOR CHAPTER 2

I.1 INCLUSION CRITERIA

Title: Understanding the knowledge and data landscape of climate change impacts and adaptation in the Chesapeake Bay region: A systematic review

Introduction: This Supplementary Material describes the selection process used to include/exclude documents from the initial sample of documents, following a systematic review process. The process is detailed below.

Phase I Each query result (i.e., link) was followed to determine whether it led to a document (i.e., PDF, Word, PowerPoint) or a website. Each result was cataloged and a PDF was downloaded or generated using an image-to-pdf internet tool. If the result led to a webpage, an evaluation was made to determine if the page contained additional relevant information to our study and the website URL was stored into a database. For scientific articles, all PDFs of all results from the Web of Science query were cataloged and downloaded.

Phase II The titles and abstracts/summaries of all search results and PDFs (omitting duplicates) were scanned for relevancy to the study. If the documents met a geographic and topic criteria then they were saved into a new folder, all other were excluded from the sample.

Phase III All the documents that passed Phase II were then read in their entirety by two team members and rated independently if a document met the geographic, topic, and data criteria. Geographic relevance meant that a document dealt with issues within Maryland and/or the Chesapeake Bay. Topic relevance refers to the extent a document's content focused on climate resilience (based on keywords searches). The final aspect of relevance was the amount of quantitative and qualitative data available in a document. Those documents that met these criteria were uploaded to NVIVO, a qualitative coding software, to perform qualitative analysis.

Document Selection and Review

We used both peer-reviewed and gray (non-journal) literature in this analysis and documents available in English. We define grey literature as documents produced on all levels of government, academics, business, and organization in electronic and print formats not controlled by commercial publishing. Peer-reviewed literature include publication in scientific and academic journals employing double-blind peer-reviews. Gray and peer-reviewed literature were obtained through different queries but both types followed a similar inclusion/exclusion criterion.

Grey literature

Data collection for grey literature initiated with the combination of keywords into 72 unique search phrases. The search was restricted to results in English and with a geographical focus in the United States. Of each search, the first 30 results were cataloged in a database. The query yielded a total of 2,100 results from Google Search Engine. All Google queries were done in incognito mode to minimize personalized search results based on a team member's search history. All Google search results were catalogued into an excel sheet.

Targeted searches were conducted on specific websites in order to expand the reach of our online search of grey literature. To do this, we constructed a database of "specialized websites and databases," which included online destinations and repositories owned or managed by government entities (e.g., federal agencies, state agencies, county government, specialized commissions), academic or research institutions (e.g., Maryland Sea Grant College, Georgetown Climate Center), or non-governmental or civil organizations that are considered key actors in addressing coastal climate resilience in Maryland (e.g., The Nature Conservancy, Eastern Shore Land Conservancy, and Chesapeake Bay Foundation) and periodically publish datasets or reports containing climate indicators.

The process of searching specialized websites involved three (3) steps: First, an initial list of specialized websites was compiled using the research team's experience in the fields of environmental decision support, environmental management, and systems ecology and previous research experience in the region. The database consisted mostly of county and municipal websites, climate and nature-focused federal agencies, and known research organizations in Maryland. Second, the database was expanded as the team performed the Google searches, where researchers flagged search results in websites that "*appeared to have other pages or resources focusing on or addressing climate resilience in Maryland*". Then, members of our team independently reviewed all flagged websites to include websites to the Specialized Database (SDB) that met our definition. Disagreements between among team members were discussed and a ranking process was developed to distinguish between majority agreement and stark disagreements. A final list was produced through consensus among team members.

We followed the methodology from Godin et al. [22], which specifies a sequential process for searching each website using a combination of (1) 'hand-searches' and (2) the use of the site's search toolbar. Given that websites included in the specialized website database ranged widely in size and focus, it was deemed appropriate to afford a certain degree of flexibility to the team members to make expert judgement as to how to proceed with each website.

I.2 CODING SCHEMA

This Supplementary Material includes all the qualitative codes that were used in our review of the literature.

Table 12: Qualitative Codes

1. SOURCE CODES	
1.1 Source Type	
Academic manuscript or paper	
Presentation	
Report	
Source - Other	
Source - Unsure	
Website or web content	
1.2 Source Authors	
Author - Other	
Government	
Local or regional government	e.g. county level
Municipal Government	
National Government	
State Government	
NGO	
Research or academic institution	
1.3 Geographic scale (document level)	
Chesapeake Bay	
County-level	
Global	
Municipality	
National	
Regional	
State of Maryland	
Unsure - geographic scale	
2. Climate change effects	
2.1 Aquatic	
Access and use	
Coastal flooding	
Ecosystem functioning and conditions	
Marine species distribution	
Ocean acidity	
Productivity	
River flooding	
Salinity	

Sea level	
Sea surface temperature	
Streamflow	
Water Quality	
2.2 Atmosphere and Climate	
Air quality	
Anthropogenic GHGs	
Humidity	
Precipitation	
Drought	
Heavy precipitation	
Temperature	
Tropical cyclones	
2.3 Built Environment	
Energy Demand and Supply	
Extent of Infrastructure	
Heating and Cooling Degree Days	
Societal	
Vulnerability of Systems to Extremes	
2.4 Human Health	
Air Quality	
Extreme Events	
Food Safety, Nutrition and Distribution	
Mental Health and Well-being	
Temperature Mortality or Morbidity	
Vector-borne Diseases	
Vulnerable Populations	
Water-borne Diseases	
2.5 Phenology	
Agriculture	
Ecosystem disturbances	
Hydrological	
Land surface	
Leaf and bloom dates	
Length of growing season	
Organismal	
Surface climate	
2.6 Terrestrial	
Ecosystem disturbances	
Ecosystem functioning and conditions	
Land surface	
Productivity and carbon storage	
Wildfires	
2.7 Adaptation	

Action accounting	
Effectiveness	
2.8 Mitigation	
Action accounting	
Effectiveness	
2.9 Economic impact of climate change	Use this to double code indicators that are discussed for their economic impact (e.g. fisheries can be presented from an ecosystem point of view or in terms of how they impact people's livelihoods)
3. Social characteristics and demographics	
3.1 Economic	
% Civilian labor force unemployed	
% Employment in extractive industries (fishing, farming, mining etc.)	
% Employment in service occupations	
% Families earning more than $200,000 per year	
% Households receiving Social Security benefits	
% Persons living in poverty	
Per capita income	
3.2 Education	
% Population over 25 with less than 12 years of education	
% Population speaking English as a second language with limited English proficiency	
3.3 Housing	
% Housing units with no car available	
% Population living in mobile homes	
% Renter-occupied housing units	
% Unoccupied housing units	
Average number of people per household	
Median dollar value of owner-occupied housing	
Median gross rent	
3.4 Population	
% African American (Black) population	
% Asian population	

% Children living in married couple families	
% Families with female-headed households with no spouse present	
% Female	
% Female participation in the labor force	
% Hispanic population	
% Native American population	
% Population living in nursing facilities	
% Population under 5 years or age 65 and over	
Median age	
3.5 Other	
4. Geographic scale (indicator level)	
Chesapeake Bay	
County-level	
Global	
Municipality	
National	
Regional	
State of Maryland	
Unsure - geographic scale	
5. Indicator data	
Existing data set	
Existing ongoing data set	
Individual data set with unknown continuation	
Existing indicator	
Existing indicator with unknown continuation	
Existing ongoing indicator	
Existing indicator categories list	Similar to a frame work but not fully built out
Existing indicator framework	
Other content	
Recommended indicator or decision aid	Code to child codes (reasons why indicators have not yet been created)
Limited Resources	
No data available	
Other reason	
Outside of document scope	
Unknown reason	
Unsure - content	
6. Indicator type	
Coincident	Coincident indicators describe the current conditions.

Lagging	Lagging indicators describe historic status and trends relative to a baseline.
Leading	leading indicators may be used to anticipate or predict future changes or impacts.
Unsure - Indicator type	
7. Resilience	Code to child codes
Exposure	amount of a community's people, assets, or ecosystems that are subject to hazard value, location, and physical dimensions, such as number of people, miles of shoreline, and property value
Hazard	potential or actual physical events that may produce damaging impacts on people, assets, or ecosystems frequency of occurrence, average, and extreme value statistics as well as characteristics of specific hazard events
Impact	result of a hazard event, taking into account the community's exposure and vulnerability.
Risk	Anything related to perceived risk or risk assessments in a certain region.
Unsure - Resilience	Use this code if you are unsure about which resilience category to apply
Vulnerability	
Adaptive capacity	ability of a community to plan and act. It influences the ability to make to changes to reduce future impacts.
Coping	ability of a community to plan and act. It influences the ability to overcome adverse conditions in the short to medium term
Susceptibility, Sensitivity	qualities of people, assets, or ecosystems that lead them to be vulnerable to a hazard event percentage of a population that is elderly or type building material and design
8. General Codes	
Conclusions - PeerRev	This node describes the conclusions on a particular article or scientific paper.
Interesting quote	
Methods	Methodology of developing an indicator - specially if there was stakeholder engagement/participation in the development process.
New Code	
Other	
Stakeholder involvement or participation	Participants involved in constructing the document. Inductively add what level of involvement

II. SUPPLEMENTARY MATERIAL FOR CHAPTER 3

II.1 ADDITIONAL STATISTICAL MODELS FOR ROBUSTNESS

Table 13: Single models for each network - (Pooled)

	(Pooled): ***Climate Change Perceptions***			
	(1)	(2)	(3)	(4)
Interaction	0.554***			
	(0.140)			
Understanding		0.642***		
		(0.196)		
Respect			0.619**	
			(0.285)	
Influence				0.446**
				(0.203)
Age	-0.012**	-0.004	-0.005	-0.005
	(0.005)	(0.006)	(0.008)	(0.007)
Gender	-0.041	-0.204	-0.236*	-0.205
	(0.109)	(0.128)	(0.140)	(0.133)
Income	0.019	0.006	0.013	0.007
	(0.024)	(0.024)	(0.027)	(0.025)
Research	0.180**	0.235***	0.267***	0.219***
	(0.078)	(0.089)	(0.098)	(0.083)
Local	0.001	-0.183	-0.112	-0.341
	(0.212)	(0.222)	(0.276)	(0.223)
t2	-0.051	-0.041	-0.036	-0.004
	(0.126)	(0.123)	(0.125)	(0.118)
t3	0.029	0.031	0.003	0.086
	(0.126)	(0.126)	(0.127)	(0.129)
Observations	121	116	116	129
R^2	0.391	0.362	0.351	0.322
Adjusted R^2	0.348	0.314	0.303	0.277
AIC	208.5796	211.3402	213.7128	236.5874

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Overview model of climate change perceptions (dependent variable) and all networks (interaction and perceptual networks).

	Predicting Perceptions of Climate Change Awareness		
	coefficient test	*panel linear*	
	(1)	(2)	(3)
Understanding	0.259	0.311	0.297
	(0.852)	(0.235)	(0.242)
Respect	1.003	-0.610**	0.036
	(0.997)	(0.275)	(0.276)
Influence	0.236	0.130	0.228*
	(0.278)	(0.130)	(0.135)
Interaction	-0.067	0.443**	0.337**
	(0.184)	(0.187)	(0.170)
Observations	84	84	84
R^2	0.478	0.279	0.399
Adjusted R^2	0.452	-0.869	0.369
F Statistic	18.114*** (df = 4; 79)	3.102** (df = 4; 32)	48.877***

Note: *p<0.1; **p<0.05; ***p<0.01

III. SUPPLEMENTARY MATERIAL FOR CHAPTER 4

III.1 GOODNESS OF FIT TESTS FOR SAOM MODELS

This section contains figures that were not included in the main article.

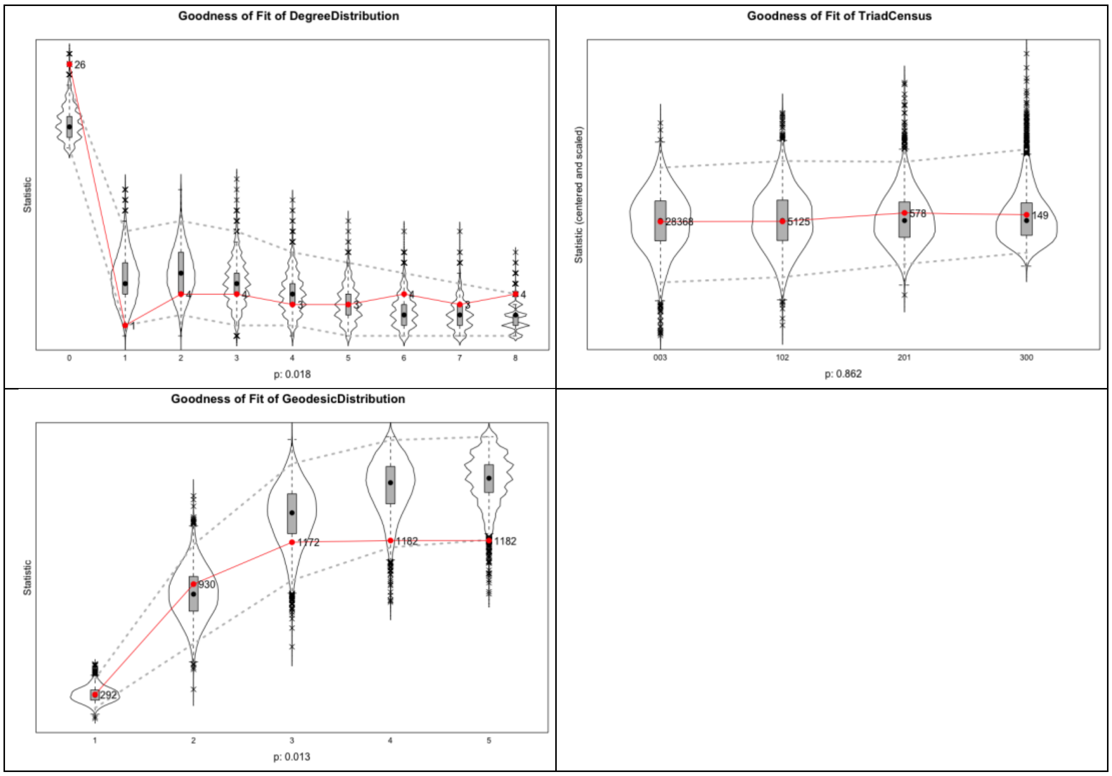

Figure 8: GOF tests for Model3a and Model 3b Period 1

Figure SM2:

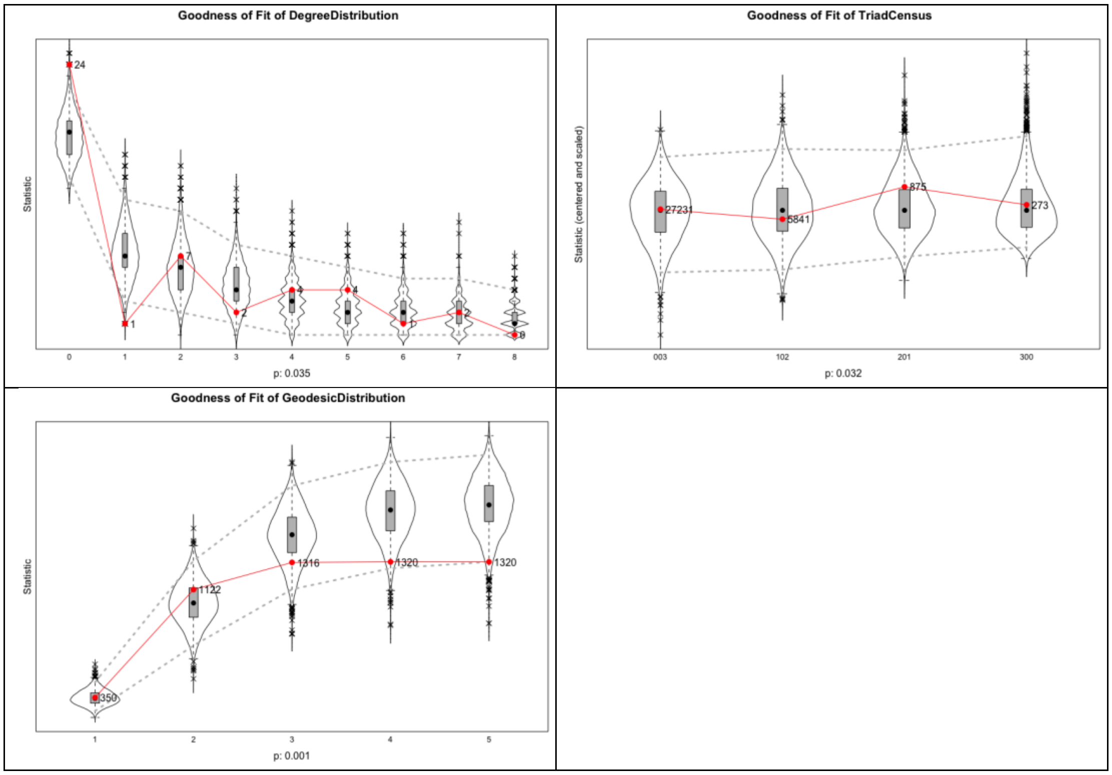

Figure 9: GOF tests for Model3a and Model 3b Period 2

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